Natural Selection, Adaptive Evolution and Diversity in Computational Ecosystems

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Abstract

The central goal of this thesis is to provide additional criteria towards implementing open-ended evolution in an artificial system. Methods inspired by biological evolution are frequently applied to generate autonomous agents too complex to design by hand. Despite substantial progress in the area of evolutionary computation, additional efforts are needed to identify a coherent set of requirements for a system capable of exhibiting open-ended evolutionary dynamics.

The thesis provides an extensive discussion of existing models and of the major considerations for designing a computational model of evolution by natural selection. Thus, the work in this thesis constitutes a further step towards determining the requirements for such a system and introduces a concrete implementation of an artificial evolution system to evaluate the developed suggestions. The proposed system improves upon existing models with respect to easy interpretability of agent behaviour, high structural freedom, and a low-level sensor and effector model to allow numerous long-term evolutionary gradients.

In a series of experiments, the evolutionary dynamics of the system are examined against the set objectives and, where appropriate, compared with existing systems. Typical agent behaviours are introduced to convey a general overview of the system dynamics. These behaviours are related to properties of the respective agent populations and their evolved morphologies. It is shown that an intuitive classification of observed behaviours coincides with a more formal classification based on morphology.

The evolutionary dynamics of the system are evaluated and shown to be unbounded according to the classification provided by Bedau and Packard's measures of evolutionary activity. Further, it is analysed how observed behavioural complexity relates to the complexity of the agent-side mechanisms subserving these behaviours. It is shown that for the concrete definition of complexity applied, the average complexity continually increases for extended periods of evolutionary time. In combination, these two findings show how the observed behaviours are the result of an ongoing and lasting adaptive evolutionary process as opposed to being artifacts of the seeding process.

Finally, the effect of variation in the system on the diversity of evolved behaviour is investigated. It is shown that coupling individual survival and reproductive success can restrict the available evolutionary trajectories in more than the trivial sense of removing another dimension, and conversely, decoupling individual survival from reproductive success can increase the number of evolutionary trajectories. The effect of different reproductive mechanisms is contrasted with that of variation in environmental conditions. The diversity of evolved strategies turns out to be sensitive to the reproductive mechanism while being remarkably robust to the variation of environmental conditions. These findings emphasize the importance of being explicit about the abstractions and assumptions underlying an artificial evolution system, particularly if the system is intended to model aspects of biological evolution.

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Contents

Chapter 1

Introduction

Darwin's theory of evolution by natural selection has undoubtedly triggered one of the most fundamental shifts in man's perception of how things come to be. Prior to Darwin, the prevalent intuition was that all things, particularly life with its astonishing adaptations and diversity, were necessarily the result of a guided design process. This view was not universal even before Darwin, but it was his great achievement to develop a coherent theory of how evolution by natural selection could create the life we find on our planet today: in a long accumulation of small and random modifications, and without the need for external design.

The implications of evolutionary theory span a wide range of areas of scientific inquiry; rarely have the insights derived from a single theory required a more fundamental rethinking of our collective world view or posed a more radical challenge to human self-conceptions. In particular, it is difficult to overstate the extent to which some of these implications are at odds with our own intuitions about design.

Evolution is a temporal process that forms its products as functional wholes. Thus, many phenomena of living things prove inaccessible to traditional attempts of functional decomposition into tidy and independent modules. In the understanding of ourselves and the natural world, only fairly recent advances have led to a process of consolidating what was long considered to be separate or even opposed; e.g., the dualisms of body and mind, and emotion and reason (Damasio 1994) are increasingly being reconciled to form a more holistic picture of the mechanisms and 'machinery' that constitute living organisms.

The intellectual heritage of this conflict and the advancement towards its resolution can also be traced in the development of the field of artificial intelligence (AI). Traditional symbolic AI followed a 'top-down' approach and focused mainly on the representation and manipulation of abstract symbols to model 'high level' intellectual skills, such as planning, problem solving and abstract reasoning (Beer 1995). By contrast, most current research in artificial agent design applies the constructive, 'bottom-up' methodologies associated with the field of Artificial Life (Alife) (Langton 1992), which emphasize situatedness and embodiment (Brooks 1991b). The terms *intelligence* and *cognition* have gradually been expanded to explain behaviour as a phenomenon arising from the interaction between agent and environment (Beer 1995) or to allow for an exploration of the role of emotions in the regulation of cognitive processes (Cañamero and Gaussier 2005, Ziemke 2008).

Evolution, as the mechanism responsible for bringing about the sought-after features in nature, is uniquely suited as a 'bottom-up' design paradigm. Most early evolutionary approaches to artificial agent design built on the extensive existing body of research on methods inspired by evolution developed since the early 1960s (Fogel 1962, Holland 1962, Rechenberg 1973). However, the practical area of application of these *evolutionary algorithms* was in the optimization of well defined combinatorial problems. These algorithms apply an artificial selection mechanism based on an explicit objective function. This objective function needs to encapsulate the *target* of the evolutionary process and often to additionally constrain the evolutionary trajectory to successfully converge on that target. The ability to devise such a function depends on the availability of a well-defined outcome and the ability to decompose the evolutionary trajectory into sufficiently small portions that can be numerically represented in this function.

In the short term and for manageable problems, optimizing a narrow set of parameters might efficiently lead to a desired outcome by constraining the dynamics of the system to more reliably and quickly follow a certain trajectory. However, the more complex the desired outcome, the more tightly the scaffolding corset of the objective function needs to be tied. The more parameters of the system are open to evolution, the more difficult it becomes to find an appropriate objective function which efficiently constrains the trajectory in the desired way. In order to reach the target, it is often necessary to evolve only some constituents of the artificial agents and functionally or structurally pre-specify other aspects with 'reasonable' guesses. In short, the results of the approach fall short of the expectations raised by its putative biological archetype.

This is not overly surprising considering that *natural selection*, the causal principle of biological evolution, plays no part in the evolutionary algorithm framework. The utility of the *artificial selection* mechanism that replaced it depends entirely on the knowledge of the designer. Thus, it could be questioned whether traditional evolutionary algorithms can really be considered 'bottom-up' design methodologies in a strict sense of the term.

Due to these limitations, it has been suggested that evolutionary algorithms based on artificial selection are unsuitable for long-term evolution of adaptive behaviour

(Packard 1989, Ray 1991b), and a number of models have been developed which operate more closely to the principles of evolution by natural selection. In systems such as *Tierra* (Ray 1991b), *LEE* (Menczer and Belew 1996b), *PolyWorld* (Yaeger 1994), or *Geb* (Channon and Damper 1998a), there is no explicit objective function. Instead, 'fitness' is implicitly modelled into the dynamics of the system. Because these models are described by the properties and interrelations between a set of agents and the environment those agents are situated in, they are referred to as evolving computational ecosystems (ECE).

Creating artificial systems which exhibit open-ended evolutionary dynamics is a high priority in Artificial Life (Bedau, Snyder and Packard 1998). Most directly, such systems would be of great practical benefit to artificial autonomous agent design. Additionally, a more principled understanding of evolutionary dynamics based on natural selection is indispensable to the task of modelling aspects of biological evolution.

1.1 Research Objectives

The central goal of this thesis is to provide additional criteria towards implementing open-ended evolution in an artificial system. There are two major challenges involved in building and analysing an artificial system capable of exhibiting open-ended evolutionary dynamics which are qualitatively comparable to those of the biosphere.

The first and most fundamental challenge results from the fact that it is still unclear, exactly what requirements a system must meet to continually produce novel forms instead of eventually converging onto a stable or 'optimal' state. Computational ecosystems based on natural selection seem the most promising candidates but, with one exception (Channon and Damper 1998a), have thus far failed to display lasting evolutionary activity (Bedau et al. 1998). The work in this thesis builds on the findings of previous models and aims to improve upon them by isolating additional criteria which are relevant for achieving open-ended evolution in an artificial system. The major focus of the approach follows the notion that to achieve open-ended evolution, the artificial system must continually generate smooth evolutionary gradients which provide possible evolutionary trajectories.

To generate dynamic evolutionary gradients, selection pressures in the developed system result from direct local competition between evolved agents (biotic selection). Biotic selection can lead to coevolutionary dynamics and ever-changing selection pressures as the success of one agent is dependent on the success of others. In practice, however, it is not enough that certain selection pressures are present. The elementary components of the system and the rules for their interaction must be defined in a way that lead to *smooth* evolutionary gradients which allow the gradual evolution of novel traits and behaviours.

The second challenge concerns the ability to understand what is actually going on in the system. This problem is of particular importance in systems based on natural selection. The lack of an explicit objective function makes the practice of rigorously analysing one particularly 'fit' agent to understand its behaviour impossible, and, as complexity and diversity across simulation runs increase, it becomes infeasible to analyse each agent in detail. Therefore, there must be some other way to identify and understand qualitatively novel behaviour when it emerges. The easiest way to achieve this, is to make the resulting behaviour interpretable to a human observer. The failure to meet this second requirement makes the analysis of a system extremely difficult as both Channon (2001a) and Taylor (1999) report for their respective systems. The system presented in this thesis aims to improve upon previous models by making qualitatively novel behaviour transparent and interpretable to direct human observation.

The main focus of the analysis of the presented model lies on the capacity of the system to effect long-term evolution of adaptive behaviour along a variety of evolutionary trajectories and on the question of how design decisions on various levels affect this capacity to generate diversity in successful strategies.

To achieve these research objectives, I will discuss the following questions:

- How do the properties and dynamics of natural ecosystems shape the evolution of the organisms they contain?
- What gives rise to complex behaviour in biological agents, and what is its function?
- What are the main design considerations to model an artificial system that recreates some of these phenomena?
- How can long-term adaptive evolution be measured and quantified?
- How does the observed complexity of agent behaviour relate to the complexity of the agent-side mechanisms subserving these behaviours?
- How can it be established that the observed behaviour is the result of adaptive evolution?
- What is the impact of design aspects on the resulting evolutionary dynamics and its products?

1.2 Contributions of the Thesis

- I provide a comprehensive discussion of the various elements of a computational ecosystem with a focus on what is required to provide smooth evolutionary gradients and diverse evolutionary trajectories.
- Based on this discussion, I describe the implementation of a computational ecosystem. The originality of the model lies both, in the novelty of specific aspects, as well as in the combination of ingredients which allow the system to continually generate smooth evolutionary gradients. The main components of the system are:
  - A mechanism that generates minimally complex agents in the sense that they contain no predefined functionality above the level of elementary components.
  - A limiting resource (energy) which is connected to each property of an elementary component in the virtual world through at least one metabolic relationship.
  - Variability operators that can affect each constitutive property of the elementary components.
  - A novel and versatile actuation model where all behaviours emerge from the concurrent evolution of form and function (as opposed to presupposing a finite set of behaviour primitives).
  - A novel reproductive criterion which decouples individual survival from reproductive success.

- I constructively show that the presented system based on these features exhibits unbounded evolutionary dynamics according to the measures proposed in (Bedau, Norman and Packard 1992). To my best knowledge, there is only one other artificial system classified into this category (Channon 2001a).
- I also show that the system generates novel, qualitatively different behaviours which are the product of a gradual evolutionary processes for orders of magnitude longer periods as compared to previous models (e.g., (Yaeger and Sporns 2006)). The fact that the qualitatively new behaviours are also easily observable is also novel with respect to previous models such as (Adami and Brown 1994, Channon and Damper 1998a, Ray 1991b, Taylor and Hallam 1998).
- I demonstrate the relevance of the introduced reproductive criterion by showing that coupling individual survival and reproductive success can restrict the available evolutionary trajectories in more than the trivial sense of removing another dimension, and conversely, decoupling individual survival from reproductive success can increase the number of evolutionary trajectories.

1.3 Outline of the Thesis

- Chapter 2 reviews existing literature on evolutionary algorithms with a particular focus on the application of evolutionary algorithms as a method to evolve neural networks (neuroevolution) as control systems for autonomous agents.
- Chapter 3 describes Darwin's principle of natural selection and the conditions under which evolution by natural selection can occur. The main body of the chapter attempts to lay out the crucial considerations for designing a compu-

tational ecosystem capable of exhibiting long-term adaptive evolution of agent behaviour. A definition of the term and of the function of behaviour is provided, followed by a description of the influence of environmental structure on the evolution of behaviour. The importance of the distinction between a behaviour and the agent-side mechanism subserving this behaviour is discussed, and possible ways of understanding how the two relate to each other are explored. A description of the term *Umwelt* (von Uexküll 1956) is followed by the development of the related argument that for an evolution system designed to exhibit long-term adaptive evolutionary dynamics, it is indispensable that the evolving entities constitute coherent, functional wholes at all times of the process. The chapter concludes with an overview of some existing computational ecosystems: a short description of *Tierra* (Ray 1991b) is provided mainly because of its importance for stimulating research in computational ecosystems; PolyWorld (Yaeger 1994) is discussed because it is the system closest to the one introduced in this thesis with respect to the interpretability of behaviours, and results can therefore, to some extent, be compared directly; finally, *Geb* (Channon and Damper 1998a) is described because it shares with the approach discussed in this text the expressed goal of creating long-term adaptive evolutionary dynamics.

- Chapter 4 introduces my model for an evolving computational ecosystem. The chapter describes the environment, the agent constituents and their interrelations which link all system components to the unitary resource (‘energy’). This is followed by a description of the reproductive mechanism which was introduced to decouple individual survival from reproductive success with the aim of increasing the number of available reproductive strategies. The chapter concludes with an overview of the algorithmic evolution mechanism of the system.

- Chapter 5 illustrates different behaviour strategies evolved in a number of simulation runs. The observed behavioural strategies are described on a behavioural level, and attempts are made to illustrate some of the agent-side mechanisms subserving the behaviours. It is also assessed to what extent the behaviour strategies are reflected in the morphological properties of the agents and the properties of the agent populations.

- Chapter 6 describes the evolutionary dynamics observed in the system. First, a measure to detect the presence of Darwinian evolution is applied (Miconi 2008b), then the Bedau-Packard (Bedau et al. 1992) statistics of evolutionary activity are implemented, and evidence is given that the system exhibits the same type of unbounded evolution as *Geb* (Channon 2001a). Finally, some general evolutionary trends in the evolution of morphological properties of several populations are contrasted with a neutral random-selection run.

- Chapter 7 describes measures of neural complexity and integration (Tononi, Sporns and Edelman 1994) which were previously applied in *PolyWorld* (Yaeger and Sporns 2006). I show that in my system both quantities increase substantially as a result of gradual adaptive evolution. I also discuss how the measured values of neural complexity relate to observed behavioural complexity.

- Chapter 8 describes the results of a series of experiments performed to assess how the choice of reproductive mechanism impacts the evolutionary dynamics of the system. In particular, the experiments aimed at identifying the influence of this mechanism regarding the available evolutionary pathways to evolve different successful behaviour strategies. The second part of this chapter contrasts the impact of the reproductive mechanism with the effect of changes on another level of the system, namely that of different resource and obstacle densities and ratios in the environment.

- Chapter 9 provides a summary of the main design considerations for the presented model, the most important results of the experiments discussed in chapters 5 to 8, and the main contributions of the thesis.

Chapter 2

Background and Related Work

2.1 Evolutionary Algorithms

Given the sophistication of structure and function in living organisms, it is not surprising that the process responsible eventually aroused the interest of engineers; the ‘bottom up’ process of evolution stands in stark contrast to the ‘top down’ design methodology of traditional engineering approaches.

Starting in the 60s and early 70s of the previous century, in close temporal proximity but presumably unrelated, several methods inspired by aspects of evolution have been developed. These methods, collectively referred to as evolutionary algorithms, derive from an engineering tradition and were originally developed as iterative search heuristics, mainly to solve combinatorial optimization problems. Therefore, the emphasis of those methods lies on finding ‘good’ or optimal solutions to well defined engineering problems. The main areas of application of evolutionary algorithms include problems where the properties of the desired solution can be precisely specified, but the search space is either intractably large or some underlying relationships

```
$t := 0$
initialize $P(t)$
evaluate $P(T)$
WHILE NOT terminate do
    $P'(t) :=$ variation($P(t)$)
    evaluate($P(t)$)
    $P(t+1) :=$ select($P'(t) \cup Q$)
    $t := t+1$
od
```

Figure 2.1: Basic mode of operation of a generic evolutionary algorithm (taken from (Bäck et al. 1997)). $P(t)$ denotes a population of μ individuals at generation t. Q is the set of all individuals considered for selection (e.g., $Q = P(t)$). By applying the variation operators (e.g., mutation, recombination), an offspring generation $P'(T)$ (also of size μ) is generated from $P(T)$. The individuals of $P'(t)$ are then evaluated according to the fitness (objective) function, and selection based on those fitness values is performed. If successful, the iteration of this process will generate fitter solutions. The algorithm typically terminates after a sufficiently good solution is found or a maximum number of iterations has been performed.

between parameters are unknown.

The three early strands were *genetic algorithms* (Holland 1975, 1962), *evolutionary programming* (Fogel 1962), and *evolution strategies* (Rechenberg 1973). Genetic algorithms were originally proposed as a general model of adaptive processes, evolutionary programming as an attempt to create artificial intelligence, and evolution strategies to solve difficult parameter optimization problems (Bäck, Hammel and Schwefel 1997). In practice, by far the largest application of all three techniques lies in the area of optimization.

Even though the various approaches vary slightly in motivation and implementation, they share the basic mode of operation. Candidate solutions (called the phenotype) for a given problem are encoded in an abstract representation (called the genotype). At the start of the process, a certain number of genotypes is randomly generated to form the initial population. Then the candidate solutions are evaluated according to an explicitly defined fitness (objective) function. The higher the fitness value, the greater the chance of a candidate to get selected for reproduction. If a candidate is selected, the genotype is either cloned (asexual reproduction) or combined with the genotype of another individual (sexual reproduction). Mutations and other possible genetic operators are applied at this stage. By repeating this process until the desired population size is reached, a new generation is created. Because the selection procedure favours those individuals which score high in fitness, over the course of many generations, 'good' genetic traits are spread throughout the population. On the other hand, less fit members of a population are less likely to be selected for reproduction, and so their characteristics tend to vanish.

In its most generic form (after (Bäck et al. 1997)), the mode of operation of an evolutionary algorithm can be described in pseudo-code as shown in fig. 2.1. Due to the amount of research on evolutionary algorithms and their large variety of application, an exhaustive review of their history is far beyond the scope of this thesis. More comprehensive reviews of methods of evolutionary algorithms as optimization techniques and the history of evolutionary computation can be found in (Fogel 1994) and (Bäck et al. 1997).

2.2 Neuroevolution

It was soon discovered that due to their ability to operate with complex, non-differentiable, and multimodal spaces (Yao 1999), methods of evolutionary computation were in many cases preferable to earlier gradient-descent-based methods for neural network training (such as backpropagation (Hinton 1989)). Considerable research has been conducted regarding evolutionary algorithms to evolve connection weights of neural networks (e.g., (Fogel, Fogel and Porto 1990)), or connection weights and topology of the networks (e.g., (Koza and Rice 1991, Miller, Todd and Hegde 1989). An early review of these efforts is provided in (Yao 1993), and a more extensive, later review in (Yao 1999).

Many early approaches employed direct mappings of genetic encoding (typically as fixed-length bit strings (Holland 1975)) to network connectivities. A *direct* encoding scheme implies that there is no essential difference in genotype and phenotype, as every connection and every neuron is explicitly specified in the genotype. This was soon found to cause problems of scalability (Belew, Mcinerney and Schraudolph 1991, Kitano 1990) in larger networks. A number of alternative, *indirect* encoding schemes have subsequently been explored. In an indirect encoding scheme, the genotype specifies rules for generating the network. Examples for indirect encoding include developmental approaches (Kitano 1990) based on Lindenmayer systems (Lindenmayer 1968), genetic programming techniques (Gruau 1996, Koza 1991b), and neuroevolution frameworks such as NEAT (Stanley and Miikkulainen 2002b,c,d). Generally, it has been found that indirect or developmental encoding schemes have a positive impact on the evolvability (Seys and Beer 2006) of neural networks, especially by allowing recurring structures to evolve (modularity) and by providing a smaller search space through compression of the phenotype to a smaller genotype (Hotz 2004, Kassahun, Edgington, Metzen, Sommer and Kirchner 2007).

2.2.1 Artificial Evolution and Adaptive Behaviour

Out of frustration with the practical shortcomings of the existing *Perception-Planning-Action* paradigm of traditional Artificial Intelligence (AI) for building robot control systems, Brooks (1986) proposed a radically different approach he called behaviour-based robotics. Instead of the conventional 'top-down' approach, he suggested a 'bottom-up' approach inspired by nature. In his subsumption architecture, complicated behaviours are decomposed into simple behaviour modules which are then hierarchically arranged in layers. The result is that the goal of each layer subsumes those of the underlying layers.

Similar realizations motivated several researchers (Beer and Gallagher 1992, Harvey, Husbands and Cliff 1993, Nolfi, Elman and Parisi 1994, Pasemann and Dieckmann 1997) to explore the potential of evolutionary neural networks for robot control. Classical AI viewed cognition purely as computation, i.e. as the "formal manipulation of quasi-linguistic symbolic representations by syntactic rules" (Beer 2003). This abstract view proved unfit for the purposes of designing simulated or physical agents that behave 'intelligently' in an actual environment. The emerging adaptive behaviour approach (Beer and Gallagher 1992, Parisi, Cecconi and Nolfi 1990) stipulated that behaviour should be seen as a property of a complete brain-body-environment system. In this dynamical system perspective (Beer 1995, Harvey, Husbands, Cliff, Thompson and Jakobi 1997, Pasemann and Dieckmann 1997), the agent represents a dynamical system which is coupled (through its sensors and effectors) to a dynamical environment. Because neural networks are themselves dynamical systems, they were deemed promising candidates as agent control systems.

Perhaps owing to its origins in robotics, but possibly in deliberate dissociation from traditional AI, most of the early research in this area (e.g., (Cliff, Harvey and Husbands 1992, Floreano and Mondada 1994, Law and Miikkulainen 1994, Reynolds 1993)) was explicitly conducted under the label of evolutionary robotics, even though, due to practical constraints, most experiments were performed in simulation (a notable early exception can be found in (Nolfi et al. 1994), where controllers were evolved on physical robots). Out of concern over not falling into the idealized 'blocks world' trap (Brooks 1991a) of symbolic AI, much effort was directed towards how these simulation results would transfer to physical robots (Harvey 1997, Jacobi, Husbands and Harvey 1995, Miglino, Lund and Nolfi 1995). Additional examples for combining neural networks and evolutionary algorithms to evolve control structures for simulated and real agents can be found in (Beer 1995, Cliff and Miller 1996, Hülse, Lara, Pasemann and Steinmetz 2001, Kodjabachian and Meyer 1998, Miglino et al. 1995, Nolfi 1998, Saravanan and Fogel 1995, Zahedi, von Twickel and Pasemann 2008). Efforts to evolve aspects of the agents' morphologies and neural controllers in simulation include (Bongard and Paul 2000, 2001, Bongard and Pfeifer 2002, Kikuchi and Hara 1998, Lee, Hallam and Lund 1996, Pfeifer and Scheier 2001), and (Funes and Pollack 1998, Lipson and Pollack 2000), where the morphologies and controllers evolved in simulation were physically built using rapid prototyping methods.

A major problem encountered when using GA methods to evolve agents capable of accomplishing a particular task is the *bootstrapping problem* (Nolfi 1998). Typically, individuals are scored against their performance (according to the objective function) in the desired task. As task complexity[1] increases, the probability that

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[1] The term 'complexity' is used here in an intuitive sense and relates to the relative 'difficulty'

first generation individuals are successful is inversely proportional to the complexity of the task (Nolfi 1998). However, if all individuals are scored with zero fitness, selection cannot operate.

There are many ways to potentially alleviate this problem. The most straightforward way is to determine heuristics about what could be 'helpful' to achieve sub-parts of the task and add suitable components to the fitness function which reward presumably beneficial behaviour or punish undesirable behaviour (Nolfi 1997). The obvious drawback of this approach is that it depends on the quality of the heuristics that can be applied and that, overall, it increases the difficulty of designing that function. Another disadvantage is that the additional constraints may restrict the trajectories available to evolution or, in the worst case may "channel the evolutionary process in wrong directions" (Nolfi 1998).

2.2.2 Incremental Evolution

Another attempt to avoid bootstrapping problems is to start the evolutionary process with a simpler version of the task and successively increase its complexity by either modifying the fitness criterion (Harvey, Husbands and Cliff 1994, Harvey et al. 1997) or the environment in which the task is performed (Chavas, Corne, Horvai and Meyer 1998, Filliat, Kodjabachian and Meyer 1999, Gomez and Miikkulainen 1997). This approach is known as *incremental evolution* and has been applied with some success. However, as shown in (Christensen and Dorigo 2006), it is also not without problems. The authors tested both versions (which they refer to as *behavioural decomposition* and *environmental complexity increase*) and found that in

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of a task.

both conditions the algorithms performed worse than in previous studies without incremental evolution. In the case of behavioural decomposition, they conclude that it might not always be possible to find a valid decomposition. Additionally, even if the desired behaviour can successfully be decomposed into distinct parts, doing so might not always be beneficial as it may prevent evolution from finding integrated, possibly more efficient solutions. The same general conclusion holds from a temporal perspective for environmental complexity increase, as high-scoring solutions are not necessarily simpler versions of successful solutions in later increments (Christensen and Dorigo 2006).

2.2.3 Coevolution

Coevolution as an evolutionary computation technique stands for the evolution of two or more competing populations with a coupled fitness. The *Red Queen Effect*[2] (Floreano and Nolfi 1997a,b, Nolfi and Floreano 1998a,b) occurs where interacting populations alter their respective fitness landscapes. Thus, an evolutionary system has to continuously adapt simply to maintain its fitness relative to the systems it is coevolving with. It has been suggested that this may result in evolutionary 'arms races' (Dawkins and Krebs 1979), where the competing populations 'drive' each other to ever increasing performance.

First attempts to use coevolutionary dynamics in simulation go back to (Barricelli 1962), but the topic only received considerable attention after later papers (Axelrod 1987, Hillis 1990, 1992, Kauffman and Johnsen 1992, Koza 1991b, Miller 1996). Over time, coevolution was successfully used in a number of different domains. Most

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[2] In Lewis Carroll's *Through the Looking-Glass* the Red Queen said, "It takes all the running you can do, to keep in the same place."

relevant to this work is the evolution of complex behaviour (Sims 1994), pursuit and evasion (Cliff and Miller 1996, Ficici and Pollack 1998, Koza 1991a, Miller and Cliff 1994b, Reynolds 1994), robot behaviour (Floreano, Nolfi and Mondada 1998, Østergaard and Lund 2003), exploration by identifying predictable novelty (Schmidhuber 1999), and the development of communication (Ficici and Pollack 1998, Werner and Dyer 1992). In addition to these works, coevolution has been applied in many other less related areas (see e.g., references in (Jong and Pollack 2004)).

Suggested reasons for the relative success of coevolutionary methods are the avoidance of biases resulting from hand-designed objective functions, the 'smoother' fitness landscapes which develop as each population adapts to gradual changes of its competitors, and the ability to escape local optima due to these changing evaluation criteria (Jong and Pollack 2004). It has also been suggested that the dynamic evaluation in coevolution may in principle lead to 'arms-races' and open-ended evolution (Ficici and Pollack 1998, Nolfi and Floreano 1998a,b, Sims 1994, Stanley and Miikkulainen 2002a, 2004).

However, there are also some problems with coevolutionary approaches. It is not well understood under what circumstances coevolution really leads to such 'arms race' dynamics (Cliff and Miller 1995, Floreano and Nolfi 1997b). In their experiments on pursuit and evasion, Miller and Cliff (1994a) have found that predator and prey sometimes adapted specifically to their opponents' current strategy without an overall increase in performance (Cliff and Miller 1996). Problems of this kind have been called *loss of gradient* (if one competing population becomes too good) (Haynes and Sen 1996), *focusing on the wrong thing* (overspecialization by exploiting an opponent's weakness instead of learning the general task), and *relativism* (if subjective fitness acts in opposition to objective fitness) (Watson and Pollack 2001).

These issues can result in cycling behaviour (Cliff and Miller 1995, Floreano and Nolfi 1997b) and mediocre stable states (Angeline and Pollack 1993). An extensive review on work with competitive coevolution is provided in (Jong and Pollack 2004), for a more recent discussion of the pitfalls and potential of coevolutionary methods see (Miconi 2009).

2.3 Computational Ecosystems

All the above methods are responses to essentially the same problem of evolutionary algorithms: for increasing task complexity it is increasingly difficult to find a fitness function which captures the relevant properties of the desired behaviour (Nolfi 1998). This is problematic even if the task is well defined. However, if the goal is to evolve autonomous agents which exhibit adaptive behaviour in a more general sense or to generate more open-ended evolutionary dynamics, it might not be desirable to specify all possible behaviours in advance.

One attempt to address this problem is to reject the evolutionary algorithm framework and model evolutionary dynamics based on natural selection. By modelling the system closer to natural evolution it might be possible to overcome some of the problems associated with evolutionary algorithms. As Ray, the creator of *Tierra*, puts it: “artificial selection can never be as creative as natural selection. The organisms are not free to invent their own fitness functions. Freely evolving creatures will discover means of mutual exploitation and associated implicit fitness functions that we would never think of.” (Ray 1991a, p. 372).

Like others (e.g., (Bedau et al. 1992, Channon and Damper 1998a, Menczer and

Belew 1996b, Packard 1989, Todd 1996, Todd and Wilson 1993, Yaeger 1994)), he considered natural selection crucial to model the creative aspects of evolution. I will collectively refer to these systems as *computational ecosystems* because the evolutionary dynamics result from the modelling of individual agents and their relations to the conditions and resources, together with their diverse interactions with other agents in their environment. The following sections discuss three such systems in more detail.

2.3.1 *Tierra* and *Tierra*-like Systems

Ray's *Tierra* (Ray 1991a,b), a computational ecosystem of self-replicating program code, was the first widely known artificial evolution system based on natural selection. His aim was to model conditions similar to earth around the Cambrian area when, from simple replicators, an explosive increase in the diversity of life occured. Even though *Tierra* didn't quite realize this goal, Ray reported some interesting evolutionary phenomena (Ray 1991b) and its success inspired several other models based on *Tierra*.

Competition in *Tierra* results from finite CPU-time and memory space. *Tierra* is based on a virtual operating system, complete with its own, relatively robust and simple (but universal) machine language and a fixed size address space. An evolutionary run starts by seeding the empty memory space with a hand-written self-replicator program. This replicator then produces a copy of itself which is instantiated as an independent process. A small amount of stochastic behaviour is implemented for program execution, the copy process, and programs are also subject to point mutations. These mechanisms are responsible for introducing variety into the populations. If the modified programs retain their ability to replicate, and the modifications alter their probability of reproduction, Darwinian evolution can occur. Once the fixed memory is filled up with programs, a ‘reaper’ (Ray 1991b) function is called which kills programs according to their age (and programs that produced errors during execution).

The evolutionary adaptations observed in *Tierra* fell broadly into two categories: *optimization* of the replication process resulting in fast reproduction, and *ecological* phenomena such as ‘parasitism’ where programs lost their reproductive abilities but were able to exploit certain mechanisms of the *Tierra* operating system to execute the code of other programs for reproduction.

Even though most of the adaptations occurring in *Tierra* have subsequently been explained as side-effects of specifically engineered properties of the language specifications (Taylor 1999), or as the result of very few mutations (Channon and Damper 2000), *Tierra* has demonstrated that it is possible to build an operating system in which self-replicating computer code can evolve. In addition to that, it sparked a number of follow-up systems based on *Tierra*.

The most intensively studied *Tierra*-like systems are probably *Avida* and *Cosmos*. The *Avida* platform (Adami and Brown 1994, Ofria and Wilke 2004) was used to study numerous aspects of evolution; issues of complexity in evolution (Adami 2002, Adami, Ofria and Collier 2000), the origin of complex features (Lenski, Ofria, Pennock and Adami 2003), and ecological stability (Cooper and Ofria 2003). The *Cosmos* platform was applied to investigate the role of contingency (Taylor and Hallam 1998) and creativity (Taylor 2002a) in evolution. A last interesting example of a *Tierra*-like system is provided by *Physis* (Egri-Nagy and Nehaniv 2003), where, in addition to self-replicating code, the language of digital organisms and the processor they run on are specified in their genomes making them also subject to mutations and heritable variation and thus enabling their evolution.

Finally, Ray himself extended the original *Tierra* platform (together with Thearling) to include multi-threaded programs running on a sixty-four processor connection machine (Ray and Hart 1998, Thearling and Ray 1994) and later proposed the fully networked version *NetTierra* (Ray and Hart 1999) which exhibited successful evolution of differentiated multicellularity.

2.3.2 ***PolyWorld***

PolyWorld (Yaeger 1994) is another early computational ecosystem and, with respect to the metaphor used to visualize evolution, it is possibly closest to the one presented in this thesis. In *PolyWorld*, haploid agents with a set of primitive behaviours (move, turn, eat, mate, attack, light, focus) populate a continuous environment containing, besides themselves, a number of energy sources (‘food’). The agents have variable metabolic rates at which they consume energy (a base metabolic rate, and a cost associated with the activation of behaviours and neural activity); they must eat food sources to survive and reproduce. The agents are controlled by artificial neural networks (ANNs) which get their input from a ‘vision system’ (a pixel map of the environment rendered from the agents’ perspective). The genome encodes certain physiological properties (size, strength, etc.) and the ANNs of an agent; the ANNs are expressed probabilistically, and synaptic strengths are adapted during the life time of the agents via Hebbian learning.

A *PolyWorld* run starts with the creation of a certain number of random seed agents. If these agents fail to establish a self-sustained population by reproduction, an *ad hoc* fitness function (which rewards eating, mating, moving, etc.) is applied to guarantee a minimum number of agents in the environment. This effectively turns the system into a steady state genetic algorithm until a Successful Behaviour Strategy (SBS) (Yaeger 1994) is found. Once an SBS has been found, this mechanism is turned off and evolution by natural selection occurs.

It is in the tradition of the 'early days' of artificial life to give very evocative names to one's creations; whatever the intentions of this practice, I believe it is not a helpful one as it can contort the perception of what is actually happening. The behaviour of the agents described in the original paper (Yaeger 1994) is rather simple and Yaeger reports that the evolved populations, for the most part, do not seem to make any use of the sensor capabilities provided. Yaeger describes three main survival strategies in detail:

- *Frenetic Joggers* primarily emerged in the wrap-around scenario. Agents with this strategy moved straight ahead, their nodes for eating and mating always activated. It is easy to see that there was not necessarily much neural computation involved in such behaviour; in fact, this could be achieved without any neural network by simply setting the biases of the three 'behaviour nodes' to negative values.

- *Indolent Cannibals* did not move much from their point of origin and killed and ate each other; they mainly evolved in simulations where, due to system configuration, creating offspring operated as a free source of energy[3].

- *Edge runners* were observed in non-wrap-around arenas where system constraints kept agents from 'falling off'. These agents ran along the edge of the world. The success of the strategy stemmed from the fact that if enough agents

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[3] The same behaviour was observed in our system when, due to a bug, creating offspring had the same effect. More than anything else, this shows that evolution is quick to exploit any unintentional imbalances and bugs in the system.

> behaved in this way, agents dying along that path would provide food sources, and the chance of finding a mate was increased.

It is difficult to determine to what extent such simple survival strategies are the result of adaptive evolution over time, as opposed to traits already present in the seed population amplified by selection. The paper (Yaeger 1994) does, however, report that at the time of writing some populations with simple associations from sensor input to motor output did evolve. However, these are not described in any detail and mainly include slowing down and speeding up in response to various stimuli.
Without extensive experience with the *PolyWorld* simulator it is hard to say why more complex behaviour using the available sensory input did not evolve. One possible reason might have been the large initial networks (200 neurons encoded in over 2000 genes) in combination with the limited computational resources available at the time. The populations were observed after only 500 generations[4], which, given low mutation rates and the large genome size appears somewhat short[5].
Unfortunately, even though research using the *PolyWorld* platform has recently been revived, the authors do not provide additional information on whether or not more sophisticated behaviours evolved in longer runs. Recent papers investigate information theoretic tools to quantify the evolution of neural structure and complexity (Yaeger and Sporns 2006), passive and driven trends in the evolution of complexity (Yaeger, Griffith and Sporns 2008), and the ecological notion of ideal free distribution (the way in which animals distribute themselves between multiple food patches) with respect to evolved agents (Griffith and Yaeger 2006).

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[4] It is not specified exactly how generations were counted.

[5] Yaeger reports (Yaeger 1994) that a run with these settings and a population size of 300 typically required 13 seconds per time step. In comparison, the system discussed in this thesis calculates hundreds of time steps per second with similar population sizes on present-day hardware.

In all recent papers the environment is initially seeded with hand-crafted 'progenitor' agents which are pre-programmed to exhibit "reasonable" (Griffith and Yaeger 2006, Yaeger et al. 2008, Yaeger and Sporns 2006) behaviours like approaching food sources and avoiding attackers; also, the simulation runs reported in those studies still seem surprisingly short (e.g., 10.000 time steps) for natural selection to have a profound effect.

2.3.3 *Geb*

Geb is an evolutionary system based on natural selection; research using *Geb* has predominantly focused on generating evolutionary 'novelty' (Channon and Damper 1998a) and evolutionary emergence (Channon and Damper 1998b, 2000). The motivation underlying *Geb* is to create a system which can "outperform its specifications" (Channon and Damper 1998a) by implementing the principle of natural selection. The contributions are intended towards developing computational intelligence rather than being a model of the real world. In this aspect it is close to the motivation of the system described in this text.

The simulated environment in *Geb* is a gridded arena populated by virtual agents with a set of possible behaviours (mate, fight, turn, move). Behaviour is controlled by artificial neural networks where specific output nodes determine the behaviour of the agents; the activations of the respective behaviours serve as inputs to nearby agents. This allows agents to acquire some information about the environment.

An interesting aspect of Geb is that the environment consists exclusively of other agents and no notion of 'energy' is used as the limiting resource. Instead, the differential reproductive success required for natural selection to operate is based solely on the competition for space; each cell of the grid can contain only one agent.

The heritable information in *Geb* encodes production rules for a developmental Lindenmayer system (Lindenmayer 1968). Agents are born with simple axiom networks that are subsequently developed according to the production rules. The bit-string label of each neuron that is used during development is also used to match the output of a neuron to the behaviour primitives and with inputs of other organisms (Channon 2001a). Due to the importance of open-ended and continuously adaptive evolution for creating computational intelligence, more recent publications using *Geb* have focused on this aspect. Measured on the basis of Bedau and Packard's statistics of evolutionary activity (Bedau et al. 1992, 1998), *Geb*'s evolutionary dynamics are, to my knowledge, the only such dynamics that classified as unbounded (Channon 2001a). Channon has subsequently extended the measure and classification system (Channon 2002, 2006) (see section 6).

2.4 Open-Ended Evolution

The ultimate goal of these computational ecosystems is to implement an evolutionary system capable of *open-ended evolution*. Informally, an evolutionary system exhibits open-ended evolution if it is capable of continuously producing novel forms instead of eventually converging onto a stable or 'optimal' state when a particular set of constraints (e.g., as defined in an objective function) is met. The requirement to produce *novel* forms implies a potentially infinite variety of available phenotypes as opposed to cycling through a finite set of possible forms (Taylor 1999).

In practice, open-ended evolution has been defined in various ways. Nehaniv (2000b), for example, defines open-ended evolution as an unbounded increase in complexity, where the method and notion of complexity applied are based in algebraic automata theory and a mathematical axiomatization of complexity developed in (Nehaniv and Rhodes 2000). The proposed definition has the benefit that it is mathematically rigorous. In (Nehaniv 2000a), possible solutions to the problem of open-ended evolution are presented but found to be “unsatisfactory” (Nehaniv 2000a) in nature. This finding leads the authors to require entities to also be increasingly embodied. Another important notion which is intimately related with this (and other) definitions of open-ended evolution is the concept of *evolvability* which Nehaniv (2005) defines as ‘the capacity of a population to generate adaptive heritable genotypic and phenotypic variation’.

Undoubtedly the most established and most applied measures for the long-term evolutionary dynamics of artificial systems are the Bedau and Packard statistics of evolutionary activity (Bedau et al. 1992). This statistical framework includes metrics for diversity, novelty, and evolutionary activity according to which the dynamics of any evolutionary system can be be classified into different categories (see chapter 6 for details). Through extensive analysis of various artificial systems (e.g., (Bedau et al. 1998)) it has been found that no artificial system exhibits the same evolutionary signature as the biosphere and only one known system (Channon 2001a) exhibits the same *class* of unbounded evolutionary activity (see chapter 6 for details). This qualitative difference between the evolutionary dynamics of artificial systems and the biosphere has led to the conclusion that possibly we are still missing some key ingredient to model open-ended evolution (Bedau et al. 1998, Bedau, Snyder, Brown and Packard 1997). However, many open problems such as the question of contingency in evolution and the question of what is inevitable in the open-ended evolution of life, respectively, could be addressed with artificial models but require them to be capable of exhibiting evolutionary dynamics which are qualitatively equivalent to those exhibited by the biosphere. Therefore, creating systems capable of open-ended evolution has been included among the most important open problems in Alife (Bedau, McCaskill, Packard, Rasmussen, Adami, Green, Ikegami, Kaneko and Ray 2000).

Most approaches based on evolutionary computation presuppose a distinction between the evolving entities and the environment they evolve in. Some have argued that pitching an evolutionary model at this level of abstraction already restricts the potential for open-ended evolution (see e.g., the discussion in (Pattee 1988, 1995, Ruiz-Mirazo and Moreno 2004)). Alternative approaches are pitched at a much lower level of abstraction and aim to model the *origin of life*. These include 'artificial chemistry' (Fontana 1991, Fontana, Wagner and Buss 1994), Kauffman's autocatalytic sets (Bagley, Farmer, Kauffman, Packard, Perelson and Stadnyk 1989, Kauffman and Farmer 1986), and computational implementations of autopoiesis (McMullin and Varela 1997, Varela, Maturana and Uribe 1974). However, while these approaches are of great interest with respect to self-organization and self-reproduction, their potential for open-ended evolution has not been clearly established (Taylor 1999).

Much earlier, the issue of open-ended evolution was also a focus of von Neumann's work. He developed his universal constructor based on cellular automata (CA) theory (Von Neumann 1966) to investigate how increasingly complicated entities could evolve from simpler ones. Based on von Neumann's original design, Langton (1984) developed a much simpler version of a CA-based self-replicator. However, he focused solely on self-replication and dropped the requirement for universal construction. Later approaches extended Langton's work and, to some extent, reintroduced the

capability to evolve into his design (Oros and Nehaniv 2007, Sayama 1999).
The open question is whether we are missing some crucial ingredients to build artificial evolution systems which exhibit the same evolutionary dynamics as the biosphere (Bedau et al. 1998). This thesis sets out to identify some additional criteria conducive for long-term evolution which help bring us closer to the goal of open-ended evolution. These considerations are then implemented and tested in a concrete computer model. The emphasis of this effort lies in improving upon previous models in two specific ways: firstly, all elements in the system and their relationships must respect the gradual nature of evolution and provide lasting, smooth evolutionary gradients. Secondly, the resulting behaviour must be easy to interpret for a human observer.

2.5 Artificial Life

Artificial Life (Alife) is concerned with the study of the processes and mechanisms underlying life by recreating life-like phenomena in software, hardware, and biochemicals (Bedau 2003). The term 'artificial life' was coined by Langton who described Alife as "a field of study devoted to understanding life by attempting to abstract the fundamental dynamical principles underlying biological phenomena, and recreating these dynamics in other physical media—such as computers—making them accessible to new kinds of experimental manipulation and testing" (Langton 1992).
The motivation and methodology of Alife can be traced back to earlier work attempting to understand the basic properties of living systems. Perhaps most prominently, von Neumann's work on self-reproducing, computation-universal cellular automata (Von Neumann 1966) and early work in cybernetics that applied information theory

(Wiener 1948) and the analysis of homeostatic processes (Ashby 1957) to the study of living systems (Bedau 2003).

However, due to the intensive use of computer simulation and the constructive 'bottom-up' approaches used in artificial life, the field has also always been tightly associated with those areas of artificial intelligence (Brooks 1991b, Holland 1975) that apply similar methods. While advances in the modelling of evolutionary or general complex systems are fundamental to both, and the two areas of research certainly have a substantial overlap, this fact can easily lead to confusion if the particular motivation of a contribution is not clearly qualified.

The main concern of Alife is to *gain knowledge about living systems* through the application of constructive methodology such as computational models of complex systems. Conversely, work in computational intelligence is typically motivated by the inverse of these propositions, namely to *gain knowledge on how to construct complex systems* through the application of knowledge about living systems.

In the case of open-ended evolution these goals can under certain circumstances converge, and advances in our ability to model long-term adaptive evolutionary dynamics of any kind are likely to be beneficial towards both ends (Bedau 1999, Channon and Damper 2000). However, especially because it is still unclear what exactly the requirements are to reproduce open-ended evolutionary dynamics in an artificial system, both approaches must build on explicit assumptions from biological theory. In this sense, this particular strand of artificial life research has considerable overlap with the field of bionics[6] (or biomimetics) which is concerned with understanding the underlying natural principles and applying them to the design of engineering systems (Nachtigall 1998).

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[6] Which is itself closely related to cybernetics (Nachtigall 1998).

Chapter 3

Natural and Artificial Ecosystems

> *We are walking archives of ancestral wisdom. Our bodies and minds are live monuments to our forebears' rare successes. This Darwin has taught us. The human eye, the brain, our instincts, are legacies of natural selection's victories, embodiments of the cumulative experience of the past.*
>
> Helena Cronin, *The Ant and the Peacock* (Cronin 1991)

3.1 Natural Selection

The earliest general evolutionary ideas on the transmutation of species and common descent date back to the ancient Greeks. Also during the 18th century, as biological knowledge grew, several naturalists proposed evolutionary ideas. However, it was Darwin (1859) who first conceived of the mechanism that could account for both, the adaptation and the diversity observed in nature. Darwin's principle of *natural selection* rests on a number of propositions (Begon, Townsend and Harper 2006):

- The individuals of a population are not identical but vary in certain traits.

- This variation, at least partly, is heritable. Therefore, an individual shares some of these traits with its ancestors.
- Every population could potentially populate the whole world if each individual of that population realized its full reproductive potential. In reality, few (if any) individuals do, and many individuals die without reproducing at all.
- Individuals vary in their number of descendants (not only the number of children they produce, but the number of children that survive, and the offspring they leave and so forth).
- The number of an individual's descendants depends critically (but not completely) on the interactions of the traits of the individual and its environment.

Populations with these characteristics, over generations, become more adapted to their environment. With time and changing circumstances, different adaptations may become advantageous. Gradually, this mechanism gives rise to different life forms. Evolution by natural selection does not make jumps from a bacterium to a rabbit in one generation. The key to adaptation by natural selection is the effect of a multitude of small but cumulative changes. But while the variation effecting these changes might be random, most of those that are preserved are not. They have turned out to be somehow beneficial to the reproductive success of their carrier.

This is the basic principle of natural selection as first described by Darwin (1859) and Wallace (1870). Since then, the theory of evolution has continuously been extended, and the role of natural selection as its primary mechanism has been affirmed (Dawkins 1996). The first step towards modern evolutionary theory was to show that natural selection is compatible with Mendelian genetics. After that, in a great and coordinated effort, the fragmented sub-fields of biology, including systematics, paleontology, developmental biology, and botany, were incorporated into the evolutionary framework to form the *modern evolutionary synthesis* (Huxley 1942). The modern evolutionary synthesis continues to be refined as new scientific discoveries emerge, but its basic tenets form the backbone of contemporary evolutionary theory.

3.2 Natural Ecosystems

An ecosystem is the complex system described by the organisms, the environment, and their physical, chemical and biological interrelationships in a given area. Ecology as a scientific discipline deals mainly with four levels of the biological hierarchy (Begon et al. 2006):

- *Organism:* How individual organisms affect and are affected by their environment.
- *Population:* The presence or absence of specific species, their numbers and trends and fluctuations in those numbers.
- *Community:* The composition and organization of populations of species.
- *Ecosystem:* The community together with its physical environment, including the pathways of energy and matter as they move among biotic and abiotic elements of the system. An ecosystem serves as a source and sink for both energy and matter.

The metaphor of an *evolving ecosystem* was chosen for this approach of artificial agent evolution because the evolutionary dynamics result from the modelling of individual agents and their relations to the conditions and resources, in combination with their diverse interactions with other agents in their environment. Together, these factors make up the artificial ecosystem. This view of an evolving system, where natural selection is an emergent system property, stands in contrast to traditional evolutionary algorithms where evolution is the direct result of an algorithmically explicit selection process.

3.3 Design Considerations for a Computational Ecosystem

As discussed in section 3.1, the principle of evolution by natural selection, as initially described by Darwin (1859) and later refined in the modern synthesis (e.g., (Huxley 1942)), is well understood and appears remarkably straightforward on the surface: natural selection operates on any populations which exhibit multiplication, variation and heredity, provided that heritable variation can affect the probability of multiplication (Maynard Smith 1987).
Continuously shaped by natural selection, life on earth has persisted for nearly 4 billion years or so (Margulis and Dolan 2002); the scale of adaptation it has undergone to persist for such a long time, to accommodate to ever changing environments and colonize the better part of the planet is hard to appreciate in its entirety. The robustness of the principle is certainly far beyond anything humans can engineer. It seems logical, then, that we not only try to fully understand how exactly evolution operates, but would seek to adopt its mechanisms and use them to our own ends.

Observing the vast variety and intricate complexity of living things on our planet,

the designer who wants to capture aspects of the process that brought these entities into existence is faced with two crucial disadvantages. Unlike nature, she can neither directly benefit from the massive real-time physics engine we call the universe, nor is she likely to have the same time frame for this undertaking as the universe allowed itself for the creation of life as we know it today.
As obvious as these two constraints might be, it seems appropriate to bring them to mind at the beginning of this section as they have major implications for every step of designing a model of artificial evolution. It is important from the outset to acknowledge the somewhat daunting reality: with respect to those two aspects, the difference in scale of operation between the universe and the designer is not a trivial but a staggering one.

The main design objective for the system described in chapter 4 was to model conditions under which long-term evolution of complex adaptive behaviour could occur. For it to be possible to evaluate the success or failure of the endeavour, several terms in this statement require careful definition. I will begin by defining how the term *behaviour* is used in this text, and what it means for a behaviour to be *complex* or *adaptive*. Finally, I discuss what kind of circumstances might lead to such behaviour in natural and artificial agents.

3.3.1 Definition and Function of Behaviour

The term ‘behaviour’ describes an observable phenomenon that results from an agent interacting with its environment (Beer 1995, Chiel and Beer 1997). Behaviour depends on all three components: an *agent* in ongoing interaction with its *environment* (there is no *eating* without *food*) and an *observer* who labels a particular segment of this interaction. From this definition follows a clear distinction between a *behaviour* and the agent-side *mechanism* that subserves this behaviour (Seth 2002). Observing the distinction between behaviour and underlying mechanism, and understanding how the two relate to each other is crucial to both designing a system 'to evolve behaviour' and being able to meaningfully interpret the subsequent results.

Because animals are products of evolution and continuously behave in all manner of ways, it is tempting to take for granted that diverse behaviour evolves in any system based on the principles of evolution. However, much research on the topic (see section 2) has shown that this is not trivially the case and that the abstractions and implementation details applied in the design of the system crucially impact the behaviour of the evolved products and of the system as a whole. To build an artificial system where artificial agents behave, we must first explicitly answer the question of *why* animals behave as they do. For the level of behaviour relevant in the present context, the teleonomic function[1] of behaviour is survival, and ultimately to increase the chances of reproductive success. A behaviour that beneficially contributes to survival and reproductive success of an organism is *adaptive*.

In the tradition of cybernetics, the 'problem' of survival can be understood as the problem of keeping a set of essential variables (e.g., temperature or blood sugar level) within a certain viable range. The adaptive function of most behaviour can thus be explained as the response of an organism to prevent the transmission of environmental variability through to its essential variables. Ashby (1957) has for-

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[1] The effect that explains its being there.

malized this principle in the *law of requisite variety* which, in its briefest (and not quite complete) form, states that "only variety can destroy variety" (Ashby 1957, p.207). Consequently, for every environmental disturbance which has an effect on the agent's essential variables, the agent must have a response to minimize this effect.

3.3.2 Relations Between Environment and Behaviour

The fundamental notion of relating the function of complex behaviour to environmental variety is shared by Godfrey-Smith's *environmental complexity thesis* (Godfrey-Smith 1998) (ECT). The ECT makes two essential claims: the first is that "the immediate role of cognition is to control behavior" and the second that "the point of this control of behavior is to deal with environmental complexity" (Godfrey-Smith 2002). However, his use of the term 'cognition' introduces another potential source of ambiguity unnecessary for the present discussion. Therefore, following Seth (2002), cognition in this context should be understood as the *regulation* effected by the (behavioural) responses of the agent to block the transmission of environmental variety through to its essential variables.

Finally, this leaves the notion of 'complexity', with respect to both behaviour and environment. The standard example regarding the perils of trusting our intuitions about the complexity of an observed behaviour is Simon's ant (Simon 1996). From the perspective of a human observer watching this hypothetical ant follow an intricate path across a beach, the ant is engaged in a complex feat of navigation. In reality, the ant-side mechanism underlying the behaviour might simply involve turning in an arbitrary direction whenever a grain of sand blocks its way. To understand the behaviour one must know the perspective of the agent (Todd and Yanco 1996) and the nature of the coupling between the ant and the environment. Thus, *complex* adaptive behaviour in embodied AI usually refers to the complexity of the agent-side mechanism subserving the behaviour (the regulation *effected* by the agent).

We might assume that natural selection does not share this interest of the AI researcher and does not invariably favour more complex agent-side mechanisms over simpler ones[2]. Indeed, we may expect selection against agent-side complexity which provides no adaptive function. This brings us back to Godfrey-Smith and the environmental complexity thesis. Godfrey-Smith considers "environmental complexity" a necessary (but not sufficient) requirement for cognition. He also offers a definition of complexity:

> Complexity is changeability, variability; having a lot of different states or modes, or doing a lot of different things. Something is simple when it is all the same. (Godfrey-Smith 1998, p.24)

This definition (besides being slightly problematic with respect to unpredictability) is not particularly concise and does not provide any concrete clues as to how to model such an environment. He goes on to clarify that the kind of environment he considers conducive for the evolution of complex agent-side mechanisms is one that provides a trade-off between environmental variability and stability in the agent-environment relations (the physical laws). Seth combines Godfrey-Smith's suggestions with the notions in (Ashby 1957) and provides a more practical definition:

> The perspectives of Ashby and Godfrey-Smith are therefore complementary, and an interpretation of the ECT emerges in which all three charac-

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[2] Chapter 7 provides a more thorough discussion of evolutionary trends in complexity.

> teristics combine: stability in distal-proximal relations, and distal variability that both threatens the agent and facilitates its activity.(Seth 2002, p.18)

Without some stability in distal-proximal[3] relations (i.e. physical laws) and distal variability that facilitates the agent's actions (e.g., the chemical gradient given off by a food source), a coordinated response of the agent is not possible. If there is nothing that threatens the agent[4], a complex behavioural response is not necessary. Therefore, "behavioural and/or mechanistic complexity can be understood in terms of mediating well-adapted responses to environmental variability" (Seth 2002).

The claim of the ECT is about necessity, not sufficiency, and the law of requisite variety (LRV) in the compacted form quoted above is incomplete. In an evolutionary context, behavioural response is not the only way to block environmental variety; in a very cold environment, for example, a warm-blooded species can respond either through a tendency to shiver, or through a thicker coat. Therefore, the compacted formulation of the LRV that 'only variety can destroy variety' does not hold in general. Distal variety can also be passively absorbed (or *buffered* (Heylighen 1992) in cybernetic terminology) through structural modifications of the system.

This realization has some relevance to building a computational ecosystem. Even if we are ultimately interested in complex adaptive behaviour, the complexity of behaviour (observed or mechanistic) is not a reliable indicator of evolutionary progress. If agents are evolved as whole systems, including parts of their morphology, evolutionary adaptation involves the whole system. If environmental variety is deliber-

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[3] Read environment-agent

[4] Because the ECT accounts for the *evolution* of cognitive capabilities, the term 'agent' should be replaced by lineage or species.

ately introduced, e.g., through scarcity or abundance of resources, possible evolutionary responses might either result in more complex foraging behaviour or simply in more economical locomotion strategies and increased resource storage (see chapter 5). Both responses can in principle be equally successful in blocking introduced environmental variety.

3.3.3 Implications for a Computational Ecosystem

If we accept Seth's interpretation of the ECT (Seth 2002), the implications of the above discussion are that an artificial evolution system designed to generate agents that exhibit complex adaptive behaviour must satisfy all three of his necessary conditions:

1. Stability in agent-environment relations
2. Environmental variability that threatens the agent
3. Environmental variability that facilitates the agent's activity

Without the third component, these conditions can more broadly be interpreted as requirements for adaptive evolution in general. Without variability that threatens the agent, adaptation is not necessary; without stability in distal-proximal relations it is not possible. It is the third component which explicitly affords an active regulation in the form of behavioural response.

To understand an animal we must understand the properties and laws that govern the relations with its current environment and those that have shaped its evolutionary history. If we disregard, for a moment, the biotic part of the environment, the stability in distal-proximal relations results from the immutable physical and chemical properties of the universe.

To complete the picture of the relations between an animal and its environment, and the environmental variability it is exposed to, it is necessary to include the biotic environment in these considerations. Considered together, the entirety of organisms, their physical environment, and the relationships that govern their interactions build a complex system. In a defined area of mutual interaction this system is called an *ecosystem* (Begon et al. 2006). Therefore, the ecosystem an animal inhabits is the smallest unit in which we can meaningfully interpret the full range of its behaviours.

In order to *explain* the adaptive behaviour of animals, the naturalist must *discover* the properties and laws that govern the complex system which created them. In contrast, the engineer who wants to *build* a complex system which generates agents that exhibit adaptive behaviour must explicitly *specify* the properties and laws of this system. Regrettably, even given complete knowledge, to attempt to faithfully model the universe down to the quantum level is not a practical option (nor a particularly useful undertaking). The more ambitious goal of Alife, to synthesize artificial life forms in order to extend the “horizons of empirical research in biology” (Langton 1988), relies on the hope that there exists a subset of conditions sufficient for ‘life’ which can be modelled computationally. For the more modest goal of building an evolutionary system to evolve adaptive behaviours, it is also necessary to understand and model the conditions which gave rise to these phenomena in nature. Even though the motivation for generating continuously adaptive dynamics in an artificial system is likely the motivation of an engineer, success or failure in this endeavour can feed back to the natural sciences. The most likely contribution to the natural sciences such an approach can make is to sharpen our understanding of complex systems in the real world.

The specific implementation of the three necessary conditions described above is the most challenging task involved in modelling a computational ecosystem. In contrast to traditional approaches of evolutionary computation, where much effort has to be directed towards the implementation details of the algorithm, most effort in an evolving ecosystem approach goes towards specifying the underlying laws and properties that define the complex system. Hence, such an approach can be considered as a move from an *evolutionary algorithm* to an *evolutionary system.* Ideally, evolution is not enforced algorithmically but instead emerges as a property of the dynamics of the system.

3.3.4 Relations Between Behaviour and Mechanism

Perhaps the most illustrative treatment of the subject of animal behaviour and mechanisms underlying it can be found in the work of Jakob von Uexküll (von Uexküll 1956). He describes the *Umwelt* of an animal as the conflation of ways in which it can *perceive* its environment and *act* on it. Uexküll illustrates his point in the flowery language of the mid-twentieth century naturalist by invoking the picture of a summer field, buzzing with beetles and fluttering butterflies; he then draws imaginary bubbles of varying sizes and shapes around each inhabitant; these bubbles are fractions of the environment containing all stimuli perceivable to the animal and thus delineating its *Umwelt.*

Uexküll's introductory example, and possibly the most famous one, is the behaviour of the adult tick. The adult tick requires the blood of a warm-blooded mammal to reproduce. To stalk its prey, the tick climbs to the top of a bush or branch; there, it waits for a mammal to pass and either lets itself be brushed off or drops down to land on its prey. If the tick is fortunate enough to land on the animal, it searches for a hairless spot where it can insert its proboscis into the flesh of its prey to suck its blood.

To the human observer this seems a surprising accomplishment for a tick; even more so when she then learns that the tick is blind as well as deaf. The behaviour of the tick, however, is only complex when interpreted through the *Umwelt* of a human. Unlike the human's, the *Umwelt* of the tick consists of only three *carriers of significance*: the light it perceives through photoreceptive cells in its skin to climb upwards to the top of a branch; the odour of butyric acid given off by the passing mammal which is the signal to let go of the branch; and finally, the body warmth which signals a hairless spot where the tick can start to suck blood. The organism is embedded in the world through *functional circles*; the perceptual cue (*Merkmal*) of butyric acid is transformed into a perceptual sign (*Merkzeichen*) which, in turn, triggers an effector sign (*Wirkzeichen*) that makes the legs let go and consequently impresses on the mammal the effector cue (*Wirkmal*) of shock. The two remaining functional circles are analogous. Thus, the whole complexity and richness of its surrounding world is collapsed into a relatively meagre structure of three functional circles—the *Umwelt* of the tick. The tick owes the robustness of its behaviour to the simpleness of its *Umwelt*; security is more important than perceptual wealth (von Uexküll 1956).

Another example can be found in the behaviour of the earthworm; it drags leaves and pine-needles down below to use for shelter and food. Most leaves will fold and offer less resistance when being pulled from the leaf tip while a pair of pine-needles will be pulled down more easily from the stalk. The earth worm reliably treats the different objects accordingly. It had originally been assumed that the shape of the leaf must carry significance in the perceptual world of the earthworm. This is not the case; experiments have shown that shape has no meaning for the earthworm; instead the perceptual sign is the difference in taste between the tip and the stalk of the leaf (von Uexküll 1956).

The discrepancy between the apparent complexity of the behaviour of Simon's ant (Simon 1996) and the simplicity of the ant-side mechanism subserving its behaviour (see last section) can now be explained as a consequence of the observer perceiving the ant's behaviour filtered through, and embedded in, her human *Umwelt*. This interpretation of the *Umwelt* has implications for understanding the relationship between behaviour and mechanism in both animals and artificial agents. Importantly, the use of the term *sign* should not be misconstrued as implying any form of explicit representation of the 'outside' world 'inside' the agent. The sign processes occurring between the receptors and effectors of the tick merely describe the agent-side part of the functional circle from which a behaviour results. Signs signify aspects of the environment that carry *meaning* for the agent. Agent-level concepts such as meaning are not incompatible with an externalist perspective on behaviour (Noble and de Pinedo 2004). The notion of *Umwelt* in relation to autonomous agent research has recently received some attention and an extensive account of its relevance is given in (Ziemke and Sharkey 2001).

3.3.5 Levels of Abstraction: Embodiment as the Construction of *Umwelt*

The ability of an evolving system to exhibit long-term adaptive dynamics largely relies on the continuity of available evolutionary pathways. In an artificial system, the level of representation, or more precisely the choice of elementary entities and rules, constitutes the complex system and determines the extent to which such trajectories are available (Conrad 1988). To avoid the introduction of design bias and in order not to unnecessarily restrict the evolutionary dynamics, Harvey et al. (1993) have argued that the level of abstraction should be as low as possible. This has been the most fundamental guideline for the choices involved in creating the system described in chapter 4.

In practice, however, there are lower limits to the choice of the adequate level of abstraction which depend mainly on the sort of behaviour that is expected of the modelled system. Von Neumann, faced with a similar problem when developing his self-replicating automata (Von Neumann 1966), was aware of this problem and argued a pragmatical position:

> If you choose to define as elementary objects things which are analogous to whole living organisms, then you have obviously killed the problem, because you would have to attribute to these parts those functions of the living organism which you would like to describe or to understand... One also loses the problem by defining the parts too small, for instance, by insisting that nothing larger than a single molecule, single atom, or single elementary particle will rate as a part. In this case one would probably get completely bogged down in questions which, while very important

> and interesting, are entirely anterior to our problem." (Taylor 1999, qtd. p.68)

Nevertheless, there are several ways in which design bias may restrict the available evolutionary pathways. The first has to do with contingency (Gould 1989); most evolutionary ecosystem implementations (e.g., (Adami and Brown 1994, Channon and Damper 1998a, Ray 1991b, Yaeger 1994)) use some form of 'progenitor' agents to seed the system. In some cases those agents are prespecified with functional structure that allows "reasonable" (Packard 1989, Yaeger and Sporns 2006) behaviour in the respective context. The intention presumably is to provide a helpful 'scaffold' for evolution; in practice this may channel the evolutionary trajectory to only explore a small area around those 'good' phenotypes and restrict a more extensive exploration of possible strategies.

A second disadvantage may result from an overly elaborate prespecified structure if it ignores the gradual nature of evolution. In most artificial systems an agent is conceptually divided into a morphology, a sensorimotor system, and a controller (usually some form of neural network). If any of these components are disproportionately complex in relation to the rest of the agent, there might be no evolutionary gradient to realize the designer's intended use for these components. Even though this has frequently been pointed out (Arbib and Cobas 1990, Cliff 1990, Harvey et al. 1993, Smithers 1994, Todd and Yanco 1996), many present approaches burden their minimal agents with excessively complex neural structure, elaborate sensorimotor systems, or highly specific morphologies which bear no relation to the complexity of the types of behaviour which are likely to evolve.

The position advocated here is that the agent has to be considered as one system and that all constituents must be allowed to evolve concurrently (starting from similar levels of sophistication). Long-term adaptive evolution can only occur if, at all times, the *Umwelt* of an agent forms a coherent, functional whole. A persistent evolutionary gradient can only exist if, starting from a simple organisation, selective pressures can effect the *gradual construction* of the *Umwelt* of an evolving lineage. The term *embodiment* (Brooks 1991b) has become increasingly important in the autonomous agent literature since it was recognized that interaction with an environment is necessary for intelligent behaviour. However, there are many different definitions of 'embodiment' which vary in emphasis and inclusiveness. The most general form of embodiment only requires some form of structural coupling (via sensors and effectors) between agent and environment[5]. More restrictive definitions require a history, or an evolutionary history of agent-environment interactions (Ziemke 2003). In robotics, definitions of embodiment typically emphasize the importance of a physical body which is sensible as a robot has to operate in the real world. However, the term embodiment is also useful for agents existing in a virtual world.

I consider an agent embodied in its respective world if, throughout its history of organization (in the case of evolution, throughout its phylogenetic history), its *Umwelt* has formed a coherent, functional whole[6].

In principle, the same argument holds for the relation between environment and agent. The predefined separation of environment and agent is understood as a prag-

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[5] This is equivalent to the term 'situatedness'.

[6] Even though Uexküll, who opposed Darwin's theory of evolution (von Uexküll 1956), would likely not appreciate this argument.

matical concession rather than a voluntary design choice. Ultimately, it would be beneficial to conceptually collapse environment and agents into a single system to complete the transition from building an evolutionary algorithm to building an evolutionary system. A similar position has been argued in (Taylor 2002b) and (Pattee 1995).

The major guidelines for the design of environment and agent components with respect to the requirements listed in the beginning of section 3.3.3, were therefore not to construct a complex environment or complex agents, but to model rich interaction possibilities between *all* system components to maximize the available number of potential evolutionary gradients.

3.3.6 Distinction Between Model and Metaphor

Due to the 'mission statement' of Artificial Life, to recreate biological phenomena or even 'synthesize' life, designers of ALife models traditionally make extensive use of biological metaphors to motivate their work and facilitate interpretation of their results. However, the thematic proximity between model and interpretation aid can sometimes be problematic. It is important to clearly distinguish the scope of the model from the scope of the metaphor; the present system is a model of evolution by natural selection and its purpose is to provide insights into the evolutionary dynamics under the particular constraints present in the system. By contrast, the concrete *behaviour of the agents* lies within the scope of the metaphor and only serves as an aid to interpreting the *behaviour of the system.* The quotation marks encasing terms describing agent behaviour like 'forage', or 'eat' are dropped solely for reasons of readability. For the same reasons that genetic algorithms are not models of evolution by natural selection, the system described in section 4 is not a model of, say, the foraging behaviour of any specific animal, even if foraging behaviour is described.

This distinction is particularly indicated in visualizations of Alife systems for two reasons; firstly, proponents of 'strong Alife' consider their systems not to model phenomena that 'behave as if' they had properties of living systems, but claim that their 'digital organisms' *instantiate* an alternate form of life (as e.g., Ray (1992) did for Tierrans). For them, then, the quotation marks could be dropped because they consider the behaviour of the agents as being within the scope of the model.

The second reason, even where no such claims are made, results from the fact that humans are terrible judges of agency and volition. We tend to intuitively associate certain properties and behaviours, like mobility, reaction to stimulus, reproduction, with living things (McCormack and Dorin 2002). Thus, without a clear distinction between these two aspects, the metaphor can reverse its intended function as an aid for interpretation and instead act as a source of confusion and thereby diminish the explanatory power of the model.

Chapter 4

Model for an Evolving Computational Ecosystem

4.1 Major Design Considerations

This section briefly lays out how the conclusions drawn from the discussion in the previous chapter were integrated into the model. Most broadly speaking, the process of designing the evolutionary system was guided by two main considerations. First, the model aims to improve upon earlier systems in that the level of abstraction at which the model is pitched should facilitate the interpretation of evolved behaviour by a human observer. The inability to identify and understand novel behaviour by human observation has frequently been identified (Channon 2001a, Taylor 1999) as a weakness of earlier attempts at open-ended evolution of increasing complexity without an explicit objective function. As the complexity of evolved behaviour increases, detailed analysis of individual agents becomes increasingly infeasible and the only way to identify and understand evolutionary innovations is by human observation of the behaviour.

Therefore, the level of abstraction and the setting of the model was chosen in a way that 'affords' certain behaviours which would lend themselves to easy interpretation. In most general terms, the model implements a basic foraging scenario where agents can move about in a two dimensional virtual world and must acquire resources to survive and reproduce. The pseudo-physics of the system are relatively simple but designed to conform to an observer's intuitions about the real world. Even though this certainly doesn't guarantee that any given behaviour is easy to understand, knowledge of the underlying rules of the system facilitates an interpretation of behaviour *'from the agents' point of view'* (e.g., movement towards food sources, avoiding of obstacles).

The second consideration concerns a commitment to the gradual nature of evolution. Continual evolution can only occur if selection pressures are present which provide an evolutionary gradient of some kind. As discussed in chapter 2 the lack of a continuous gradient was the main driver behind the development of the various methods of evolutionary computation. In a traditional genetic algorithm, the evolutionary gradient is provided by the objective function. Agents are evaluated against this function and evolve (usually in isolation) until some stable or optimal configuration is reached, at which point evolution stops and the population converges. Because the selection pressures result from a fitness function or the interaction of an agent with its environment, this type of selection is referred to as *abiotic selection*. The complement to abiotic selection is *biotic selection*, where selection pressures result from the direct interaction with other biota (the evolving entities, or agents). Channon (2001a), for example, importantly stressed that the distinction between abiotic and biotic selection is more crucial for open-ended evolution than the distinction between artificial and natural selection. Only direct interaction and competition with other evolving entities can induce dynamic, non-stationary selection pressures which can lead to coevolutionary dynamics and the lasting availability of evolutionary gradients.

In addition to the presence of evolutionary gradients, open-ended evolution requires that these gradients be relatively smooth. Thus, the elementary components of the system and the rules for their interaction must be defined in a way that allows the gradual evolution of novel traits and behaviours. To this effect, the presented model aims to improve upon earlier systems in several ways:

- *High structural freedom*: The agents exist in a continuous world, all action and perception is continuous and all effects of morphological properties are governed by continuous relationships. The elementary components of the agents are defined in a very generic way; effectors, sensors and neural circuitry can be placed and combined arbitrarily to allow an infinite number of possible agent configurations. Additionally, initial agents have no predefined functionality above the level of elementary components. This aims to reduce possible discontinuities in the fitness landscape introduced by such designer bias (Funes and Pollack 1997, Nolfi 1998).

- *No predefined behaviour primitives*: in most previous systems (e.g., (Ackley and Littman 1992, Channon and Damper 1998a, Halavati and Shouraki 2002, Menczer and Belew 1996a,b, Werner and Dyer 1992, Yaeger 1994, Yaeger and Sporns 2006)), agents adapt to choose from a predetermined and finite set of behaviour primitives which are presumed relevant for survival. These actions are typically fixed outputs of the controller which are activated at the appropriate times to initiate the corresponding behaviour. On the one hand, as mentioned above, this might introduce discontinuities in evolutionary gradients while the agent population struggles to adapt to the specific scaffolding provided by the designer (Nolfi 1998). On the other hand, and more importantly, as pointed out by (Channon 2001a, Taylor 1999), a finite set of possible actions "constrains organisms around these actions and so limits evolution."(Channon 2001a). The model presented thus aims to improve upon earlier systems by forgoing such predefined behaviour primitives. Instead, action is based on a versatile actuation model. Locomotion is the only form of actuation used. However, as with all other elementary components, locomotive effectors can be arbitrarily placed and combined to allow a wide range of body plans and thus implement the various forms of higher behaviour usually provided by behaviour primitives. The gradual and concurrent evolution of morphology and control, of the underlying mechanisms responsible for the observerd behaviour, is consistent with the discussion in chapter 3 and allows the lineages of agents to gradually shape their *Umwelten*.

- *Decoupling of individual survival and reproductive success*: one of the most important features of the model is the decoupling of individual survival from reproductive success which gives the evolving entities control over when and to what extent they invest resources into offspring. This is claimed to increase the diversity of viable strategies and generate more biotic selection pressures as different populations may follow different reproductive strategies (see chapter 8 for simulation results and a thorough discussion of the topic).

The system contains certain elements which provide abiotic selection pressures which are of particular importance early in a simulation run while no stable population of agents has yet been established. These include the need to acquire energy in order to reproduce and survive as well as the danger of colliding with obstacles in the environment. These selection pressures gradually change in character as sustained populations of agents emerge. The abiotic pressure of simply finding energy sources is eventually superseded by the biotic pressures resulting from direct competition for these sources with other agents. With increasing population size, also the threat of colliding with static obstacles is exceeded by the threat posed by other agents. Thus, as an evolutionary run proceeds, abiotic selection pressures are largely displaced by changing biotic pressures which are claimed to provide more sustained evolutionary gradients and therefore allow long-term evolutionary activity and innovation.

4.2 Introduction

The system view that needs to be adopted in the design of a computational ecosystem makes it difficult to describe the environment, the agents, and their interrelations as conceptually separate entities. These conceptual distinctions, to the extent that they are valid in the real world, are not as easily applied to a system that is entirely artificially constructed. We can only refer *quantitatively* to the composition of an environment (e.g., the availability of food sources) on the basis of the physical laws that define the *qualities* of the objects contained in this environment. Therefore, the ability to describe a real environment as a separate concept results from the universal and immutable laws of physics and from the relationships these laws effect. In contrast, in an artificial universe with arbitrary rules it makes no sense

to refer to one object as an ‘obstacle’ and to another as a ‘food source’ without describing the underlying rules which confer these qualities to them and thereby legitimate such labelling.
To facilitate both the description of the model and the interpretation of the resulting dynamics, the abstract physical laws underlying the system were defined in a way that aims to preserve the causal coherence with an observer’s intuitions (e.g., the way in which colliding objects are deflected) while at the same time ensuring computational tractability. The implementation of those rules constitutes the foundation for the three requirements (see 3.3.3) that are hypothesized to enable the evolution of complex behaviour.

The central metaphor of the artificial world revolves around a notion of ‘energy’. Based on the underlying laws, the environment acts both as a source and a sink for energy. Energy is also the resource on which the agents’ survival and reproductive success depends. It is the only direct resource in the artificial world (as opposed to e.g., space). All objects in the environment and all constitutive agent components are *grounded* in this world through at least one relationship to energy. These interrelations between energy and components provide the required stability in the agent-environment interactions. They also define the trade-offs that generate the available evolutionary trajectories to gradually construct the agents’ *Umwelt*.

Adaptation by natural selection operates by many small but cumulative changes to its products. The gradual principle of evolution is violated if some parts of the system contain functionally predefined structure disproportionate to others. At best, this limits the evolutionary trajectories available and, at worst, it makes an evolutionary approach impractical (hence the difficulties of evolving neural controllers for real robots (Funes and Pollack 1997)). For these reasons, the agents in this model have no functionally predefined structure on levels higher than the elementary components. Instead of pre-defined behaviour primitives (e.g., turn, fight, etc.), all behaviour is based on simple but versatile locomotive effectors. Thus, starting from minimal, arbitrary configurations, agents are evolved as coherent, functional wholes.

4.3 Environment

The simulation environment is a continuous toroidal arena. In addition to agents, it contains two different kinds of objects: *energy sources* and *obstacles*. All objects carry information (variability that *facilitates* the agents' actions) about their solidness ρ, their energy signature e^t at time t, their current velocity v, and whether or not they are an agent $a \in \{0, 1\}$. These properties constitute the perceivable modalities in the simulated world. The energy signature indicates the amount of potentially consumable energy at time t. Solidness determines whether an agent can pass through an object ($\rho = 0$) or whether it collides with it ($\rho > 0$).

An energy source has a given maximum energy capacity $c > 0$ which defines its initial energy content. If an agent is in contact with an energy source, a certain amount of energy is transferred from the source to the agent and thereby consumed. The energy content of a source cannot fall below zero and 'grows' back to its capacity at a constant rate. Energy sources have an energy signature equal to their current energy content, a solidness of zero, and a radius equal to their energy signature. Throughout the simulation, they are relocated to random positions with a certain probability.

An obstacle is an object with zero energy capacity ($c = 0$) but non-zero solidness. The radius of an obstacle equals its solidness. To avoid 'clustering' over evolutionary time, obstacles are immovable. If an agent collides with an obstacle it bounces off and loses an amount of energy proportional to the deflection from the impact.

4.4 Artificial Agents

Like all other objects in the environment, an agent's body is also defined by its solidness ρ and size r. For agents, however, ρ and r are heritable parameters which affect and shape their metabolic dynamics. With these parameters, we can define a virtual *'mass'* m:

$$m = \rho r^2 \pi \tag{4.1}$$

which determines the maximum amount of energy an agent can absorb (*energy capacity*) $c = \sqrt{m}$ and the rate $\lambda = \mu_\lambda(1 + m)$ at which it can absorb energy per time step (μ_λ is a constant). The capacity of an agent determines its base metabolic rate (see 4.4.2). The relationship between mass and metabolic rate is implemented as a power law similar to the allometric scaling law which can be observed in animals (West, Brown and Enquist 1997). The mass of an agent also has implications for other energetic costs; the amount of energy needed for locomotion increases linearly with mass and the damage (loss of energy) an agent sustains in a collision is also influenced by its mass. The damage in a collision is proportional to the magnitude of the deflection from the impact. This means that, in a head-on collision with a stationary obstacle, a fast agent receives more damage than a slow one and a 'light' agent takes more damage than a 'heavy' one.

Agents are created with a life energy $l = 0.5c$. They can increase this energy up to their maximum capacity by consuming energy sources and lose life energy according to the metabolic model (see section 4.4.2). An agent dies if its life energy is less or equal to zero. In this case the agent is replaced with a 'corpse object'. A corpse object is similar to an energy source, with the difference that its energy content 'decays' over time. The energy signature e^t of an agent equals the energy content of the corpse object should the agent die at this time, which in turn equals the energetic cost for reproduction (see section 4.4.3).

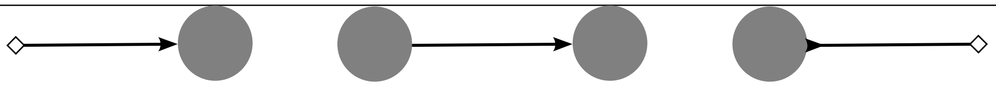
4.4.1 Sensing and Acting

As in many comparable systems, I use a form of neural network to map sensory input on effector output. The network consists of nodes (neurons) and directed connections. A node is defined by the tuple $N = \{k, b, d, \phi\}$, where k is a heritable parameter defining the slope of the transfer function, b is a heritable bias and d and ϕ specify the position of the node in polar coordinates relative to the agent's center. The output O^t of a node i is defined as:

$$O_i^t = \tanh\left[k_i\left(\sum_{j\in N_i} w_{ij}O_j^{t-1} + \sum_{m\in S_i} s_{im}I_m^t\right) + b_i\right] \tag{4.2}$$

where N_i is the set of all nodes j with synaptic inputs w_{ij} to i and S_i is the set of all sensory connections s_{im} to perceptible stimulus I_m. The transfer function is an adapted version of the one used in (Husbands, Smith, Jakobi and O'Shea 1998).

In contrast to many other models, sensors and effectors are themselves connections of the neural network. A connection is defined as the tuple $L = \{w, p, \phi, N_{in}, N_{out}\}$,



(a) An open connection feeding into a node functions as a sensor.

(b) A connection which is connected to nodes at both ends functions as a traditional synapse.

(c) A connection which is open on its downstream side works as an effector.

Figure 4.1: Sensor-controller-effector mapping consists solely of nodes and connections. The connection mode determines the role of a connection in an agent.

where w is the weight of the connection, p the *channel*[1] it operates on, ϕ specifies the angle of a locomotive effector (and is ignored otherwise), and N_{in} and N_{out} the input and output nodes respectively. The connectivity pattern of a connection defines its role (fig. 4.1); a connection between two nodes functions as a traditional synapse (the channel p is ignored) of the neural network. One that is only connected on the output side is a sensor at the position of its projecting node N_{out}; the *channel* p defines the stimulus it responds to. Finally, a connection which has an input node N_{in} but no output node functions as an effector; effectors can either be reproductive (see section 4.4.3) or locomotive. Thus, a connection can take one of three roles: synapse, sensor or effector (see fig. 4.1).

Locomotive effectors can be thought to act like small jets or flagella (see figure 4.2). An agent can possess any number and configuration of these effectors which allows for flexible locomotion strategies. A locomotive effector is defined by its position on the agent's body (the position of N_{in}) and the angle ϕ it makes with it. This allows us to calculate a rotational and a translational component proportional to the activation of the effector. The integration over all effectors yields the overall movement of the agent.

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[1] In a sensor, for example, the *channel* specifies the modality (solidness, energy, etc.) the sensor responds to.

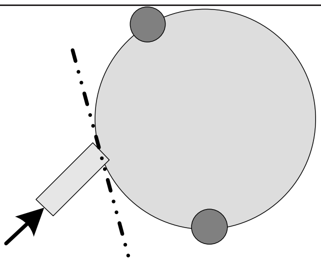

Figure 4.2: Exemplary body of a first generation agent with two sensors (round) and one effector (arrow indicates impulse direction).

A sensory connection can perceive external or internal stimuli depending on the channel p it responds to. The four external channels are solidness, energy signature, velocity, and the presence of other agents; the internal channels are life energy level and reproductive depot level. For internal sensors, the activation passed to the connected node is simply the normalized value of the internal property scaled by the connection weight. External sensors can intuitively be imagined as measuring a chemical gradient (see figure 4.3); the activation $A^t_{i,p}$ of a connection i sensitive to channel p is the sum over the influence of a particular channel of all objects within a maximum range:

$$A^t_{i,p} = w_i \sum_{j \in O} \frac{o^t_{j,p}}{1 + (d^t_{i,j})^2} \tag{4.3}$$

where O is the set of objects within the maximum range, $o_{j,p}$ is the value of property p of object j, and $d^2_{i,j}$ is the squared distance between the object and the sensor.

4.4.2 Metabolism

As indicated in the previous section, the energy budget of an agent is influenced by the properties of its body and its behaviour. At every time step a certain amount of energy is subtracted from the agent's life energy. The first part is the 'structural'

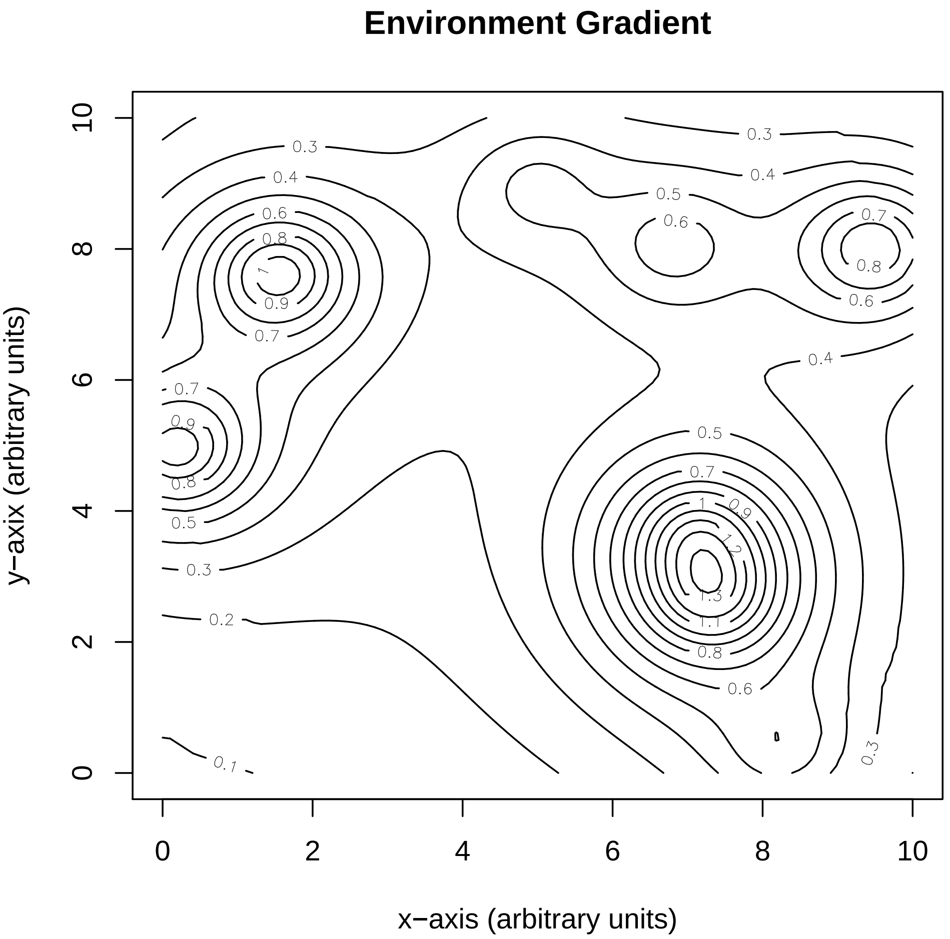

Figure 4.3: Extract of an exemplary environment. All object properties (solidness, energy signature, velocity, agent) constitute information modalities which can be perceived as an environmental gradient by sensors that respond to the respective modality. The intensity of the stimulus is inversely proportional to the square of the distance between sensor and object.

cost $\kappa = \mu_c c + \mu_s \sqrt{2N + L}$, where c is the energy capacity of the agent, N and L are the number of nodes and connections, respectively, and the two μ are proportionality constants (note that the structual costs follow the same power law for increasing

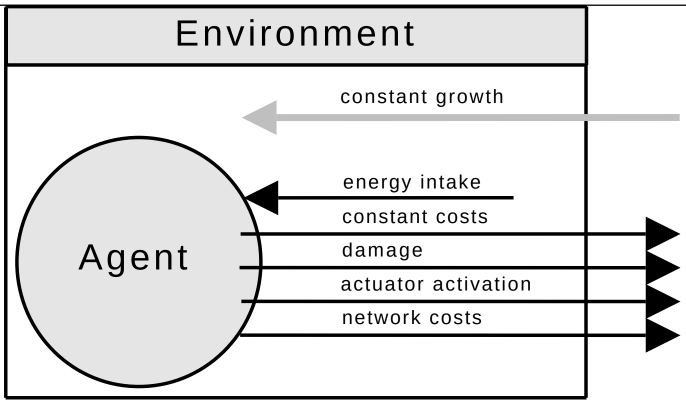

Figure 4.4: Total energy balance of agents and environment. The environment acts as source (regrowth) and sink (agent consumption) for energy.

network size as for increasing capacity). This part is constant over the life time of the agent and captures body properties and network size. Additional costs are variable and consist of locomotion costs (effector activation in proportion to mass) and information processing costs (accumulated node activation). These relationships between the agent and the environment define the dynamics and create the selection pressures in this artificial ecosystem. All survival-relevant capabilities (sensing, acting, information processing, energy storage) carry an energetic cost (and potential benefit). The balance of these aspects defines the various trade-offs and enables the agents to follow varying strategies to successfully acquire and manage resources and generate a sustained population.

The energy balance of the agents and the renewal (energy sources) and decay (corpses) of resources determine the total energy budget of the ecosystem (illustrated in Fig. 4.4), which is updated every time step. The ecosystem is not a closed system with respect to energy; energy is added to the environment and dissipates via the metabolic consumption of the agents described by the following equations:

$$l^{t+1} = l^t + \Delta e^t - \Delta d^t - \kappa - C_o^t - C_a^t \tag{4.4}$$

with:

$$\begin{aligned} C_o^t &= \sum_{i \in N} a_i^t \cdot \mu_{co} && (4.5) \\ C_a^t &= \sum_{j \in A} a_j^t \cdot \mu_{ca} && (4.6) \end{aligned}$$

where l is the life energy level of the agent at time t, Δe is the energy consumed, Δd the energy lost to collision damage, κ are constant costs, C_o are the costs for node activation a over all nodes N, and C_a are costs for effector activation a over all effectors A. The two μ are proportionality constants set by trial and error with the goal of balancing the influence of each aspect so as to have a significant impact, while still allowing evolution to occur.

The energy content E of an energy source s at time $t+1$ is:

$$E_s^{t+1} = E_s^t - \sum_{a \in A'} \Delta e_a^t + \mu_g \tag{4.7}$$

where a is an agent in the set A' of all agents which have consumed an amount of energy Δe from source s at time t. The energy content of a source cannot be negative. This equation also holds for corpses if the constant growth rate $\mu_g > 0$ is replaced by a decay rate $\mu_d < 0$.

4.4.3 Reproduction

An evolutionary system based on natural selection in which, unlike in biological evolution, self-reproduction is not an emergent, self-organized property of the physics (Kauffman 1993) of the system, requires some condition under which agents are to reproduce. The choice of reproductive mechanism can potentially have a large impact on the dynamics of the system (see section 8), somewhat similar to the effect of the choice of fitness function in a genetic algorithm.

Many simulated ecosystems, including the one presented in this paper, are based on some notion of energy. The flow of energy through the system, determined by the relations defined by the designer, defines the constraints and the selective pressures for the evolutionary process. The success of the evolved agents depends largely on their ability to acquire and manage this energy resource (indirectly, space is also a limited resource). Therefore, also the reproductive mechanism should be directly or indirectly linked to energy. We define the cost ψ for reproduction as:

$$\psi = 0.6c + \mu_s \sqrt{2N + L} \tag{4.8}$$

where c is the capacity of the agent, N is the number of nodes and L is the number of connections of the controller (neural network). Note that the reproductive cost is larger than the agents' initial life energy ($l = 0.5c$). Agents must, therefore, consume energy before they can reproduce and reproduction does not 'create' free energy.

In addition to locomotive effectors, agents can possess reproductive effectors. Whenever such an effector is activated, an amount of energy proportional to the activation is transferred from the agent's life energy to its *reproductive depot*. If the reproductive depot exceeds the threshold ψ, the agent reproduces (and the reproductive depot is set to zero). The idea behind this is to decouple individual survival from reproductive success. Even though the agents still have to collect energy in order to survive and reproduce, this reproductive mechanism gives the agents full control over *when* and to *what extent* they invest in reproduction. Thus, agents have to actively invest their *life energy* into creating offspring. Doing so jeopardizes their own survival because the invested energy is no longer available to them and reproducing creates a direct competitor in the vicinity. On the one hand, one might think that this would eventually lead to zero investment in reproduction. In this case, evolution would cease to happen or, in fact, never happen at all. On the other hand, however, it is clear that, in dynamics based on natural selection, the notion of selecting *for* zero reproduction is contradictory as reproduction is the very vehicle of selection. Additionally, in an environment where individual survival is to some degree dependent on chance, and thus effective immortality is unachievable, an infertile population is unsustainable and will inevitably go extinct.

4.5 Evolution Mechanism

Reproduction in this system is strictly asexual. Whenever an agent reproduces, a possibly imperfect copy is placed close to the parent. For natural selection to work on the agent population, two more ingredients are still missing: variation and heredity.

The only source of variability in the system is mutation, and mutation operators are defined for *all* parameters of an agent and its neural controller network. Ad-

ditionally, mutation operators exist to add or remove nodes and connections. This allows for the evolution of arbitrary and recurrent network topologies and parameter configurations.
The last property necessary for evolution is heredity. Much work in computational models has focused on encodings for evolving artificial neural networks (for an extensive overview see e.g., (Yao 1999)). A large part of this work has investigated the impact of the encoding of the neural networks on their evolvability (e.g., (Seys and Beer 2006)), and various frameworks to efficiently evolve neural networks have been proposed (Mattiussi and Floreano 2007, Stanley and Miikkulainen 2002a). While there is no final consensus on what the optimal encoding should be, the main lesson from these studies is that the encoding crucially impacts the evolvability of the evolutionary system. In this model, no special encoding is used, and all mutation operators are performed directly on the agents' object structure. The reason not to use a more sophisticated network evolution method was to keep the system as simple as possible where no further complexity was needed.

Adaptation in this system occurs solely on an evolutionary scale through reproduction. Agents do not change or adapt during their lifetime. However, change on an evolutionary scale can only happen if a *turnover of generations* exists, i.e. agents must reproduce and pass their heritable traits to their offspring. In a classical genetic algorithm, this turnover is an inherent property which is explicitly enforced by the artificial selection mechanism; no matter how poorly initial seed agents perform, some will achieve relatively higher fitness scores than others. This is not the case in systems based on natural selection. If initial 'seed' agents do not successfully reproduce, no evolution can occur.

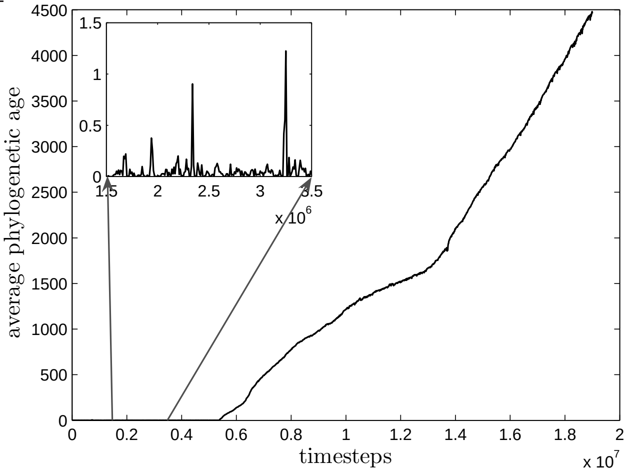

Figure 4.5: Development of the average phylogenetic generation (PG) of a population over an exemplary run. The inset shows cases of extinction early in evolutionary time where all inheritable material is lost.

There are several ways to solve this problem in practice; in Tierra (Ray 1991b), and Tierra-like systems (Adami and Brown 1994), initial seed agents are generated with the hard-coded functionality for reproduction; in *PolyWorld* (Yaeger 1994), an *ad hoc* fitness function is applied until agents are sufficiently adapted to maintain a population. I take a different approach: the environment is seeded with agents without any kind of predefined functionality. Seed agents are generated with random body and network configurations. To track the existence of a generational turnover, a *phylogenetic generation* (PG) was assigned to each agent. Initial seed agents have a PG of zero, their offspring a PG of one, and so on. To guarantee a certain number of agents in the environment, I use a mechanism called MEAM (minimum enforced agents mechanism). The MEAM monitors the population and ensures that a certain number of seed agents are always present in the environment. In the beginning of a run, the entire population consists of such seed agents. If the probability of randomly creating an agent which can survive long enough to reproduce is greater zero, the MEAM will eventually seed a population which can be maintained by self-reproduction. Figure 4.5 shows an exemplary development of the average PG of an agent population. Early in an evolutionary run, when the agent's survival and reproductive success is more governed by chance than any well-adapted strategy, extinction can occur if the whole population dies out. In this case, all heritable material is lost and evolution has to start over. However, in the conducted experiments this rarely happened (and then mostly very early in a run). Once a population reached a certain number of agents and spread across the environment, total extinction did not usually occur. Hence, for nearly all runs, maximum PG is increasing nearly monotonically.

Population size is not fixed or constant, but only constrained by the fact that the amount of energy in the environment is limited, and by the metabolic properties of the evolved agents. Once a self-sustaining population is established, the MEAM merely functions as a source of noise and generally has little effect unless this population goes extinct; in this case the whole process essentially starts 'from scratch'. For all the experiments presented in the next sections, the MEAM was set to keep a minimum of 15 seed agents in the environment. The resulting main program loop of the system is described in figure 4.6.

```
do forever
   all objects ← update()
   FOR all agents do randomly
      IF energy $> 0$
         agent ← update()
         IF depot $> R_T$
            agent ← reproduce()

      ELSE add corpse ← agent
   od
   WHILE # agents $< A_{min}$ do
      createAgent()
   od
od
```

Figure 4.6: Pseudocode showing the main program loop of the evolutionary system. At every time step all non-agent objects are updated. Next, agents are either updated and reproduce if their reproductive *depot* exceeds their reproductive threshold R_T, or replaced with a corpse object if their energy is less or equal to zero. Finally, if the total number of agents is lower than a set minimum A_{min}, an appropriate number of random agents is created (MEAM).

Chapter 5

Experiment I: Behaviour Relates to Morphology

5.1 Introduction

The primary purpose of this chapter is to give a general impression of the behaviour strategies that populations evolved across different runs of the system. It introduces the types of these strategies with respect to agent behaviour and morphology. As discussed in chapter 4, the initial agents generated by the MEAM have no predefined functionality above the level of elementary components. They are created with a small number of arbitrarily configured components and random body properties. Most of these agents cannot survive or reproduce. However, one of those agents eventually succeeds in founding a sustained population. From this point on, natural selection can shape certain behavioural strategies and the populations gradually become adapted to their local environment and to the particular strategy they follow (Todd and Yanco 1996). Over evolutionary time, the individuals in the population become more embedded in their environment as evolution continuously constructs their *Umwelten*. Therefore, comparable to the evolution of different animals, the differences in lifestyle across various populations should be manifest in both the observable behaviour as well as the morphological properties of the agents.

The elementary components and relationships in this system were defined in a way that was hoped to generate rich evolutionary dynamics and provide a large number of available evolutionary trajectories. In the absence of an objective function, there are no predefined tasks against which the performance of the system can be measured. The absence of any clues about what the observed behaviour might signify would severely complicate an interpretation of the simulated evolutionary dynamics. However, a system based on an intuitively meaningful metaphor greatly facilitates the interpretation of the observed behaviours (Channon and Damper 2000, Taylor 1999). A useful metaphor allows an interpretation of (many) behaviours on the agent-level without restricting the freedom of the model on the level of the mechanisms which subserve these behaviours. The metaphor based on a foraging scenario chosen for this system *affords* certain agent-level behaviours whose function can easily be understood without the need to fully appreciate the underlying mechanisms. In the concrete context, successful populations might exhibit behaviours such as actively approaching energy sources or actively avoiding obstacles. This ability to interpret the behaviour on the agent-level greatly facilitates the task of analyzing how those behaviours are realized on the level of the mechanism. Therefore, the two levels of description are complementary (Noble and de Pinedo 2004). In the following discussion of evolved populations I attempt to address both levels. However, because the agent-level descriptions better convey the general nature of the evolved behaviours I focus on this level in this overview chapter (issues of mechanistic complexity are discussed in more detail in chapter 7). Additionally, due to the relatively high structural freedom provided by the model, the mechanisms underlying similar behaviours vary greatly in the details of their implementation. It is therefore debatable how much could be learned by discussing each of those mechanisms in great detail.

5.2 Experimental Setup

To obtain the results discussed in this chapter, the simulation was run in relatively small 100x100 unit arenas (minimum agent size is 0.1 units) with 35 energy sources and 35 obstacles. Energy sources had an energy capacity of 1.0 and obstacles a solidness of 1.0. Objects were randomly placed in the environment following a uniform distribution. The simulation was repeated 85 times using different random seeds for the random number generator which determines object placement, initial agent configuration and all mutation operators. The minimum enforced number of agents was 15 in all 85 runs. Since in this setup there is no obvious 'convergence point', simulations were run until the average phylogenetic generation (PG) of a population was above 1500 or a set maximum time was reached (80 hours). From each of the 76 'successful' runs (where a sustained population was established) a sample of the first 100 agents of PG ≥ 1500 was taken.

5.3 Results: Behaviour and Morphology

In 76 out of 85 runs, the MEAM (minimum enforced agent mechanism) eventually established a sustained population and evolution could occur. Actual computation time to reach this point depended greatly on a number of factors: the moment a sustained population was established, the average population size, the complexity of the average controller network, and the average lifetime of the individual agents. While in some runs a sustained population was established almost immediately, in 9 runs it did not happen at all before the maximum time was reached. These runs were discarded. A general observation was that as could be expected with the relatively small population size, all populations were quite homogeneous within a single run. One reason for that is that all agents within the population of one run were ultimately descendants of one respective *founder* agent which spawned the initial population. Other possible reasons are that the environments were rather small (an agent could travel 'around the world' frequently during its lifetime) and both obstacles and energy sources were uniformly distributed. In the following sections I will describe some of the evolved agents, their behaviour and their morphologies[1]. All agents in this experiment exhibited base movement (movement in the absence of stimulus). For the first part of the analysis of the results, three basic evolved behaviour patterns are distinguished solely by observation of evolved populations:

- *Energy response:* agents show *some* response (e.g., slowing down) in the presence of or in contact with an energy source.
- *Energy approach:* agents change direction and actively try to approach an

---

[1] For better illustration, videos of the various behaviours can be found on this website: http://homepages.feis.herts.ac.uk/∼pp6bs/ or on the CD-ROM accompanying the dissertation.

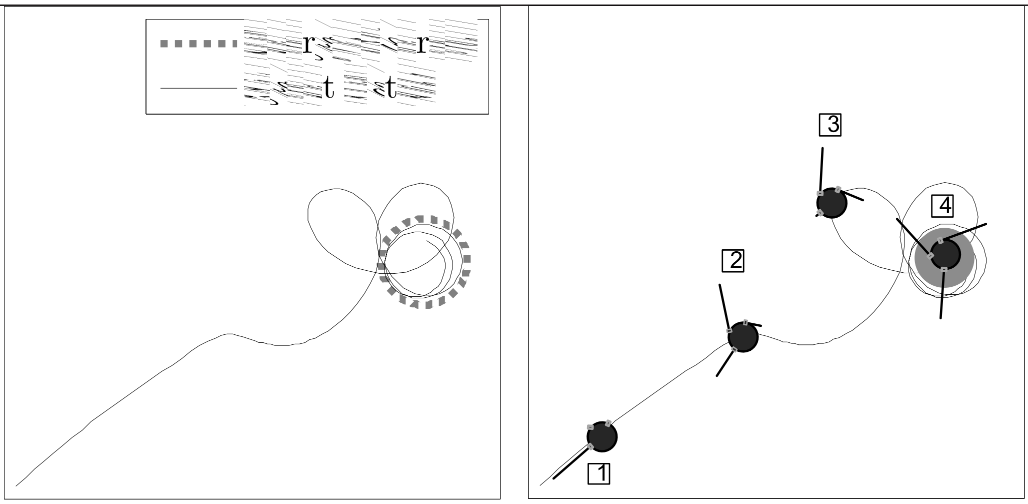

Figure 5.1: Path of Agent approaching an energy source (left). The illustration on the right gives an impression of how this behaviour is achieved. (1) only one effector is active (the length of the line shows the activation intensity), creating a straight movement, (2) the agent perceives the energy source for the first time and begins circling (3) the agent still circles but the main effector is now completely inactive (4) the agent positioned itself in the centre of the energy source and rotates on the spot.

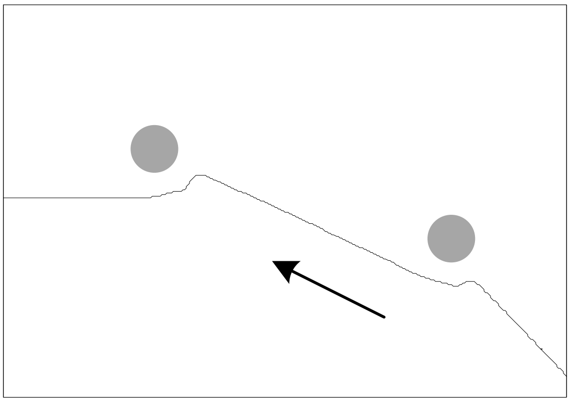

Figure 5.2: Path of an agent avoiding two obstacles. The arrow indicates the path direction and the two obstacles are illustrated as circles.

energy source (see figure 5.1).

	ER	EA	OA
Drifter	yes	no	no
Forager	yes	yes	no
Avoider	yes	no	yes
Allrounder	yes	yes	yes

Table 5.1: Classification of agents by the three observable behaviour patterns: ER (energy response), EA (energy approach), and OA (obstacle avoidance).

- *Obstacle avoidance:* agents change their behaviour in the presence of an object of non-zero solidness (see figure 5.2).

The definition of these behavioural patterns is intentionally careful. If an agent changes its behaviour in response to an obstacle, it might do so in a way that will generally increase the probability of avoiding a collision. However, those mechanisms are not perfect and in some situations the behavioural change of the agent might actually cause it to hit the obstacle even harder than without any change. Because behaviour is the result of an interaction between the agent and the environment (see section 3.3.1), no observer would speak of the resulting behaviour as obstacle avoidance if the agent actually makes the impact worse.

I have classified the agent strategies into four basic kinds, based on the three behavioural patterns identified above (see Tab. 5.1). Overall, agents of the same class share essential behavioural tendencies, even though they vary in the details of their implementation. Figure 5.3 shows the morphological properties of the four agent classes, categorized by behaviour patterns, and Fig. 5.4 shows differences between agent categories on the population level. It is interesting (though not surprising) to note that even though the categorization was done solely on the basis of behavioural observations, it is nearly perfectly reflected in the body properties of the agents. As could be expected, it turns out that if both body and controllers are evolved as a

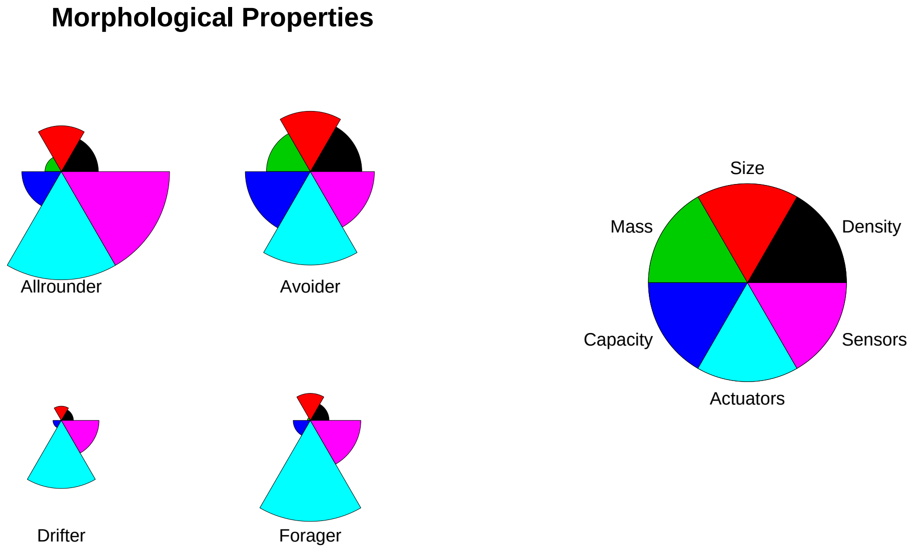

Figure 5.3: Morphological properties (all normalized to 1) of evolved agents (PG 1500) categorized by behaviour patterns. Drifter agents are smallest, have the lowest solidness, and the fewest network components. Foragers are similar to drifters with all values slightly increased. Allrounders have more sensors and a higher energy capacity (through increases in size and solidness). Finally, Avoiders have slow base movement which allows (and requires) a significantly larger energy capacity (through increased size and solidness).

functional unit, one cannot discuss one without the other. The evolutionary dynamics shape the complete agent and adapt it to a certain survival strategy.

5.3.1 Drifters

Drifters exhibit relatively fast base movement using their (usually) single functional locomotive effector. With a single effector an agent cannot change its direction, it can only modulate its speed. Consequently, drifters can neither avoid obstacles nor actively approach an energy source. Instead, they modify their speed in the presence

Figure 5.4: Average population size (left) and average population age (right) of evolved agent populations categorized by behavioural strategies. Error bars show the 95% confidence interval. The large bars for avoider populations are due to the small sample size (3).

of an energy source. They achieve this either by ‘monitoring’ their life energy supply and stopping if it exceeds a certain threshold, or by using energy sensors to measure the energy concentration of the environment. Whenever the energy concentration is high, they slow down or come to a complete stop. Drifters are typically very small and light-weight (see Fig. 5.3). Their life span is comparatively short but their population size is larger than that of all other types (see Fig. 5.4). Drifters usually only have one sensor, one (functional) effector and minimal networks to control their extremely simple behaviour. In many simulation runs, the first sustained population consists of drifter-like agents. Sometimes they evolve into other types, but often a relatively stable drifter population establishes itself where only the morphological properties are further refined to suit this strategy. It is worth noting that even this simple strategy requires a fair amount of adaptation to first acquire and then ‘calibrate’ the required sensory and actuation system. No viable strategy emerged where output was constant (e.g., comparable to ‘always go forward and kill’, reported in (Channon and Damper 1998a)).

5.3.2 Foragers

Foragers have base movement, change their behaviour in the presence of an energy source, but do not avoid obstacles. In their simplest form, a single energy sensor and one effector placed roughly opposite the one responsible for base movement are sufficient to perform successful approach behaviour. The translational component of the base effector is counteracted by a usually slightly tilted second effector. This results in an inward spiraling movement dependent on the strength of the sensory stimulus. However, the experiments show that usually two energy sensors and a larger number of effectors are used to implement this behaviour. Also the actual behaviour resulting from the agents’ actions and its robustness vary from population to population and over evolutionary time. Some agents will always manage to approach an energy source within their sensor range while others may only succeed if they are approaching from a particular side. Another difference is how well an agent is able to keep contact once it has approached the energy source. While some agents spend most of the time ineffectively circling around an energy source, others can perfectly center themselves over it and remain there until the source is either fully consumed or disappears.

While drifters usually minimize their body size to the lower bound of 0.1, foragers almost consistently have a size of about 0.3 (see Fig. 5.3). Some foragers also increase their solidness instead of their size. Both adaptations lead to higher capacity but also higher movement costs. Foragers have to find energy more often than drifters, but also consume energy sources more efficiently.

5.3.3 Avoiders

Avoiders follow a somewhat surprising strategy. They are the only agents that completely abandon energy perception through external sensors. Avoiders exhibit base movement and obstacle avoidance. The different populations responded to contact with energy sources in different ways. In all cases the resulting behaviour can be explained by the internal sensor for the agent's life energy level. In the first case the base effector of the agent is inhibited once its life energy level exceeds a certain threshold and the agent stops on top of the energy source. In the second case the same trigger activates the effector used for obstacle avoidance, causing the agent to start moving on a perfectly circular trajectory. In both cases the agent (at least partly) consumes the energy source without directly sensing its presence. The respective behaviour patterns persist even if the energy source disappears until the life energy level drops below the triggering threshold. Avoiders have slower base movement than other agents. This seems to be an adaptation their consumption strategy as there is a considerable delay between first contact with the energy source and the life energy reaching the threshold needed to trigger the agent's response. The observed avoiders are bigger than foragers and have a higher solidness. The increased solidness gives them a much larger capacity at a medium risk because of their obstacle avoidance capabilities.

5.3.4 Allrounders

Allrounders are agents which exhibit all three behaviour patterns. Basically, they are the same as foragers with the added ability to avoid obstacles. Their foraging behaviour is the same and they can sometimes evolve from forager agents. However, they tend to have a higher capacity than basic foragers. Most of the evolved allrounders achieve this by increasing the solidness value. As with avoiders, the risk of increasing the solidness is lowered by the ability to avoid obstacles. Allrounders (as can be expected) have the most complex networks and the most sensors and effectors. They also have the smallest population sizes.

5.3.5 General Properties

To show that behavioural diversity emerges even in simple and uniform environments, I have only discussed four survival strategies. However, it is worth noting that changing the number of obstacles and energy sources in the environment can lead to different behavioural strategies. I will mention one observed type of agents because of their radically different approach. This particular strategy evolved in response to environments with high concentration of both obstacles and food sources. A high concentration of obstacles 'penalizes' movement early in evolution when agents are not yet well adapted (e.g., by either being light-weight or by avoiding the obstacles). There, agents can be nearly or completely sessile. These agents exhibit no base movement at all. They remain stationary until an energy source appears within their sensor range. Once in range, they quickly approach the energy source, center themselves over it and remain there. These agents have much larger bodies and simpler controller networks than mobile agents. Larger size consumes a lot of energy when moving, but it also increases the maximum energy capacity of the agent. A larger agent which does not move can survive longer without consuming energy.

More generally, however, selection seemed to favour small and light-weight agents that exhibit some base movement early in evolution. This is further optimized if agents follow the drifter strategy. Agents with an active foraging strategy (foragers and allrounders) are slightly larger and agents with slow base movement are even larger still to increase their energy capacity. All agents without collision avoidance minimize solidness. Agents with collision avoidance often increase solidness and size to increase their energy capacity. Sensors are effectively restricted to the required minimum while effectors seem to accumulate even if they are not used efficiently or not at all (see Fig. 5.3).

Reproductive strategies are very hard to analyse in detail as they can only be understood by analyzing the dynamics of each agent's network. Supporting the rationale behind our reproductive criterion which gives the agents control over *when* they invest in offspring, constant reproductive activity (irrespective of internal and external circumstances) did not emerge as a viable strategy in a single sustained population.
However, most agents follow simple reproductive strategies or combinations thereof; these can roughly be summarized as follows: Invest in reproduction if energy is present, otherwise don't. There are different ways to achieve this. The most commonly used is a positive correlation between energy sensors and the effector for the reproductive depot. Alternatively, the activation of the reproductive depot is posi-

tively correlated to either the internal energy level or the activation of a locomotive effector used for foraging. Many agents use a combination of these strategies. Additionally, often a negative correlation between a solidness sensor (or an effector used for collision avoidance) and the reproductive activity exists.

5.4 Discussion

I have shown data of four distinct behavioural strategies evolved in a virtual ecosystem. The different types of agents evolved ‘high level’ behaviours (foraging, obstacle avoidance) without a discrete set of predefined behaviour primitives and without any other pre-defined functionality or structure above the level of the elementary components. All behaviour is the result of the agents interacting with the environment via a very simple but versatile locomotion model. Evolution occurred in an artificial ecosystem by natural selection, and both neurocontrollers as well as morphologies (size, solidness, sensory and actuation structure) of the agents were freely evolved. The results of these more general experiments show that this approach is indeed capable of evolving diverse behaviour while further reducing the need to preconceive necessary behaviour primitives that the agents might need to survive under different environmental conditions. To keep evolved strategies comparable, I have only used a small and homogeneous environment in this experiment. Also, I have only discussed some of the most frequently occuring behaviour strategies. Other behaviour strategies which were only rarely observed (and of course possible behaviours which were not directly observed due to the large amount of data) were not considered in this first analysis.

The initial classification of the different behavioural strategies was carried out solely by visual observation of evolved populations. Subsequent analysis of both morphological and population properties has shown that this classification is reflected in these properties. This is a positive and expected result which confirms that the populations of agents evolve as functional wholes which are gradually adapted to the strategies they follow. Evolutionary trends in the adaptation of phenotypic characteristics will be further discussed in section 6.4. Furthermore, these findings are of practical relevance in chapter 8 because they allow to quantitatively assess the diversity of evolved behaviour strategies across populations evolved under varying conditions.

The discussion of evolved behaviours has concentrated on individual agent behaviours and largely neglected ecological phenomena. Even though the design of the system was intended to allow a range of collective behaviour and ecological interactions (e.g., predator-prey dynamics and food-webs) such behaviour was rarely observed. One explanation for this could simply be that such complex ecological relationships simply did not regularly evolve due to the fact within a single run all agents followed similar strategies and belonged to the same lineage.

However, another explanation could be that ecological interactions did evolve but I failed to observe them. Such a failure to identify behaviour would likely have resulted from the same difficulties with interpreting behaviour as were encountered by Channon (2001a) and Taylor (1999) during the analysis of their respective systems. It is easily possible that many ecological interactions simply could not be identified by casual observation. The diversity and complexity of strategies and the large amount of data makes even the rigorous analysis of individual agents infeasible, and certainly much more so the analysis of all ecological relationships between the agents, particularly when it is unclear how these relationships might look. Therefore, mainly for the simple reason of the limited time I could devote to analysing each run in detail I have focused the discussion on some examples which could reliably be observed and were easy to identify across different runs.

Also, regardless of whether complex, direct ecological interactions did not evolve or merely were not observed does not imply a lack of biotic selection pressures or coevolutionary dynamics. These pressures also result from indirect interactions through the competition for energy and space in the shared environment as every sub-lineage of agents with a beneficial trait has changes the chances of survival and reproduction for other agents.

5.4.1 Note on the Experimental Data

The data presented in this chapter and in section 6.4 were obtained using an older version of the model than the one described in chapter 4. The major difference between the two versions are that the old model was based on a more restrictive sensor-network-effector model and included some predefined structure above the level of elementary components. The new model also includes a more sophisticated pseudo physics engine which makes the system behaviour more coherent with an observer's intuitions about the real world (e.g., how colliding objects are deflected) and is computationally more efficient. The main reasons for these changes were to make the model conceptually simpler while at the same time increasing computational efficiency. The details of the older model are published in (Pichler and Cañamero 2007) and can be found in appendix A.

However, this does not affect the relevance of this discussion of evolved behaviour for the following chapters. All observations on the level of the different categories of agent behaviour presented in this chapter are the equivalent between the two versions of the model. The main difference in result between the two models concerns the distribution of evolved agents between the various behaviour categories. While most populations generated by the old version followed the Drifter strategy, populations evolved in the new version are mostly Allrounders. The new model thus has a higher probability of generating behaviour strategies which are behaviourally more complex than the old model version.

Chapter 6

Experiment II: Evolutionary Trends and Activity

6.1 Introduction

Due to the lack of an explicit fitness function in an evolutionary system based on natural selection, there is usually no straightforward way to evaluate ‘progress’. Even more so because such systems are typically designed with the aim of creating long-lasting, adaptive evolutionary dynamics and not to evolve agents that perform well in a particular task. The focus is on the *process* more than on a particular *solution.* Because these systems are complex systems which necessarily include specific design choices, their dynamics are not easy to understand. This makes it difficult for the designer to interpret her results and even more so to meaningfully communicate them.

The system described in chapter 4 implements an arbitrary ecosystem which is based on real world intuitions to facilitate interpretation by a human observer. This can be helpful to get a first impression of whether or not adaptive evolution is taking place by visually observing the temporal development of the system. However, in such cases in particular, there is a certain danger of unconsciously transferring assumptions that hold for the *modelled* system to the model system. In a model of evolution, for example, one of these 'traps' might be that one tends to assume that most changes in the agents occur as adaptations to selective pressures present in the environment. Therefore, given sufficient complexity of the model in question, in most cases of artificial evolution one can legitimately ask whether what is observed is indeed adaptive evolution guided by the presence of selective pressures, or simply the result of random variation and stochastic effects inherent in the dynamics of the system.

Several methods have been proposed to measure various aspects of adaptive evolution. For example, Adami et al. (2000) calculated the per-site entropy of an agent's genome to measure evolution in terms of the complexity of evolved agents in *Avida* (Adami and Brown 1994). Another complexity based measure called "exhibited evolvability" was proposed in (Nehaniv 2000b). The measure relates to the rate of increase of complexity in a population. Their notion of complexity is based on a measure introduced earlier in (Nehaniv and Rhodes 2000). Finally, using a dynamical system approach, (Burtsev 2003) proposed a measure based on the movement of the system in the "genome phase space".

6.2 Bedau and Packard's Evolutionary Activity Statistics

The most widely used measures for evolutionary activity are the Bedau and Packard statistics (Bedau et al. 1992, 1998). The main idea behind these statistics is that adaptive evolution can be quantified by the persistence of certain components over evolutionary time. The authors summarize the rationale behind the method as follows:

> Our evolutionary activity statistics are computed from data obtained by observing an evolving system. In our view an evolving system consists of a population of components, all of which participate in a cycle of birth, life and death, with each component largely determined by inherited traits. (We use this "component" terminology to maintain enough generality to cover a wide variety of entities, ranging from individuals [sic] alleles to taxonomic families.)
>
> Birth, however, creates the possibility of innovations being introduced into the population. If the innovation is adaptive, it persists in the population with a beneficial effect on the survival potential of the components that have it. It persists not only in the component which first receives the innovation, but in all subsequent components that inherit the innovation, i.e., in an entire lineage. If the innovation is not adaptive, it either disappears or persists passively. (Bedau et al. 1998, pp.228)

Evolutionary activity thus aims to identify adaptive innovations in an evolutionary process. An innovation (new component) is considered adaptive if it persists and if it continues to be used. In practice the activity of a component is calculated by attaching counters to all components to track their persistence over time.

To visualize the effect of the selection process, a random-selection model which 'shadows' the actual run is computed beside the real simulation. To obtain the shadow data, for every 'birth' in the real run a randomly chosen individual of the shadow population is reproduced, and for every 'death' in the real run a random agent is removed from the shadow population. The shadow run mirrors the real run, except that selection is random.

The concrete implementation of the Bedau-Packard statistics requires the calculation of the activity $a_i(t)$ for each component i, the diversity $D(t)$ (number of components present at time t), the total cumulative evolutionary activity $A_{cum}(t)$, the mean cumulative evolutionary activity $\bar{A}_{cum}(t)$, and finally, the new evolutionary activity per component $A_{new}(t)$. The simplest and most general activity increment is given by:

$$\Delta_i(t) = \begin{cases} 1 & \text{if component } i \text{ exists at } t \\ 0 & \text{otherwise} \end{cases} \tag{6.1}$$

The remaining quantities are calculated as follows:

$$\begin{aligned}
a_i(t) &= \begin{cases} \sum_{k<t} \Delta_i(k) & \text{if component } i \text{ exists at } t \\ 0 & \text{otherwise} \end{cases} && (6.2)\\
D(t) &= \#\{i : a_i(t) > 0\} && (6.3)\\
A_{cum}(t) &= \sum a_i(t) && (6.4)\\
\bar{A}_{cum}(t) &= \frac{A_{cum}(t)}{D(t)} && (6.5)\\
A_{new}(t) &= \frac{1}{D(t)} \sum_{i:a_i(t)\in[a_0,a_1]} a_i(t) && (6.6)
\end{aligned}$$

The values of a_0 and a_1 should be chosen in a way that A_{new} captures new evolutionary components of adaptive significance. I chose the value of $a_0 = 10^7$ as the highest component activity in the shadow populations so that $A_{new} = 0$ for the shadow. The value for a_1 is set to a_0 plus the sampling increment (10^5), so that every new component can only show up once in the statistics for A_{new}.

Choosing the components is a bit more difficult in the present system. The Bedau-Packard statistics are easier to implement if heritable information is represented in discrete rather than real values (Bullock and Bedau 2006). To avoid having to define a metric of 'similarity' of different parameter values, I have decided to take only neurons and synapses (including sensors and effectors) into account. As discussed in chapter 4, no genetic representation is used in this system, and agents are copied directly from the object structure of the parent. Every component generated by the MEAM receives a unique ID which is passed on when the component is copied from parent to offspring. This method of defining components renders the measure blind towards some mutations (e.g., modifications of node parameters). Therefore, the activity values can be expected to be higher than if they were calculated on the basis of single parameters while at the same time new activity might be lower because only the adding of neural structure is counted towards evolutionary novelty. However, because neural structure is added and removed by mutations, the rationale behind the evolutionary activity statistics is not violated by this choice.

Figure 6.1 shows the averaged evolutionary activity statistics of ten runs of the system. The mean cumulative activity is unbounded[1] for the real run and bounded

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[1] The definition for (un)boundedness given in (Bedau et al. 1998) is: The function $f(t)$ is unbounded *iff*:

$$\lim_{t \to \inf} \left(\frac{\sup(f(t))}{t} \right) > 0$$

where sup(.) is the supremum function.

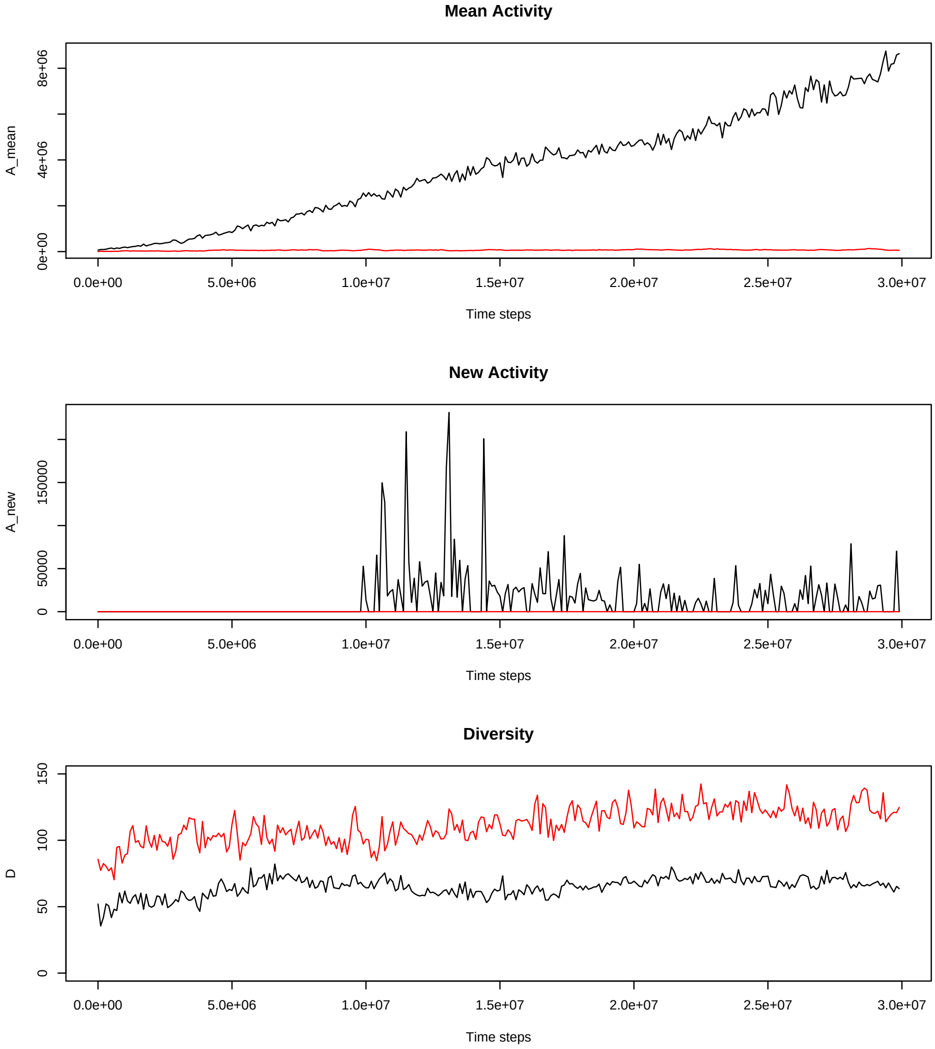

Figure 6.1: Mean cumulative activity, new activity, and diversity averaged over 10 simulation runs. The evolutionary dynamics of the real run (black) fall into class 3b (unbounded) and those of the neutral shadow (red) into class 1 (none).

for the neutral shadow run. Mean new activity is positive[2] for the real run and zero

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[2] Also taken from (Bedau et al. 1998), the applicable definition of positive is: The function $f(t)$ is positive *iff*:

$$\lim_{t \to \inf} \left(\frac{\int_0^t f(t)dt}{t} \right) > 0$$

Table 6.1: Classification of evolutionary dynamics and their statistical signatures (classes 1-3a based on (Bedau et al. 1998) and classes 3b and 3c extended by (Channon 2001a).

Class	Evolutionary Dynamics	D	A_{new}	$\bar{A}_{cum}$
1	none	bounded	zero	zero
2	bounded	bounded	positive	bounded
3a	unbounded (D)	unbounded	positive	bounded
3b	unbounded ($\bar{A}_{cum}$)	bounded	positive	unbounded
3c	unbounded ($D \& \bar{A}_{cum}$)	unbounded	positive	unbounded

(as per choice of a_0) for the neutral shadow. As could be expected, the diversity is bounded for both the real and the neutral shadow run. According to the extended classification system proposed in (Channon 2001a) and described in table 6.1, the statistical signature of the evolutionary dynamics of the system fall into class 3b. To my best knowledge, *Geb* (Channon 2001a, Channon and Damper 1998a) is the only other artificial system documented which also falls into this class, even though numerous systems have been evaluated using these measures. Among other artificial systems for which evolutionary activity statistics have been calculated are *Tierra* (Ray 1991a) and *Tierra*-like systems including *Cosmos* (Taylor 1999) and *Avida* (Adami and Brown 1994), *Echo* (Holland 1975), *Bugs* (Packard 1989), *Eco-Lab* (Standish 2000), and the evolution system described in (Arthur 1994). None of these systems classify as unbounded (Bedau et al. 1997, Bullock and Bedau 2006, Channon 2001a) in the extended classification system (table 6.1).

Bedau states that "creating such a system is among the very highest priorities of the field of artificial life" (Bedau et al. 1998, p.197)[3], and certainly a system that generates adaptive evolutionary dynamics over a prolonged period of time must nec-

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[3] He was referring to class 3 dynamics in his classification which is equivalent to class 3a dynamics in the classification used here.

essarily fall into the third category. Even though this is an important step, being classified as class 3 dynamics is more likely about necessity, not sufficiency, depending on what we expect of such a system. I share this view with Channon who, after his system 'passed' this test, cautioned against undue enthusiasm over the result (Channon 2001a) and proposed some modifications to the method (Channon 2002). Moreover, the suspicion that classifying as category 3 is necessary but not sufficient is supported by the study reported in (Miconi 2008b) (see section 6.3 for details). Nevertheless, if we accept that natural selection is indeed operating in this system (for further evidence see next section), the evolutionary activity statistics allow some interesting observations about its dynamics. Firstly, the unbounded (at least for the observed period) mean cumulative activity is a very encouraging result, particularly because the system is based on asexual reproduction alone. Due to the lack of horizontal transfer of heritable material, asexual populations are susceptible to phenomena like 'mutational meltdown' (Gabriel, Lynch and Burger 1993) (also referred to as *Muller's Ratchet*), where deleterious mutations accumulate over time and eventually lead to the extinction of the lineage. Because the population usually consists of one lineage (see section 5), the extinction of this lineage would 'reset' the evolutionary activity statistics. Therefore, the results show that lineages persist over long time periods where adaptive evolution can occur. Secondly, the bounded diversity is also a direct result of the fact that only one lineage is usually present in one run. With one lineage, and because neural components carry a high metabolic cost (see section 4.4.2), it would have been a disturbing result had the diversity turned out to be unbounded. Finally, and perhaps most interesting is the positive new activity. The graph confirms[4] that a continuous addition of novel structure

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[4] The late onset of positive new activity is a result of the relatively high threshold ($a_0 = 10^7$).

occurred. This is perhaps the strongest indication yet of lasting adaptive evolution in the system.

6.3 Fitness Transmission

As mentioned in the last section, Miconi (2008b) has recently pointed out that the Bedau-Packard statistics are most effectively used when the presence of a non-random selective process has already been established because he reports situations where random selection processes can lead to 'false positives'. Miconi proposed a very simple measure he calls *Fitness Transmission*, which he claims to be more reliable to verify the presence or absence of adaptive evolution. This measure is complementary to the Bedau-Packard statistics because it allows fewer qualitative conclusions about the observed evolutionary process. To substantiate the evidence for the presence of evolution in my system, I will briefly summarize the *Fitness Transmission* measure and give some results below.

In a nutshell, fitness transmission measures the correlation between the fitness of individuals and their parent(s) to give an indication on whether or not fitness-relevant traits are being transmitted across generations. A persistently positive correlation implies the presence of non-random selective pressures. To ensure that these fitness scores are obtained under similar conditions, the genealogical record is divided into discrete time slices, and only individuals from the same slice are compared. The fitness of an individual equals its number of grandchildren (NOGC). Unfortunately, the NOGC of an individual and the NOGC of its parent(s) are not statistically independent, and the necessary normalization proposed by the author (for every parent-child pair subtract the child's children from the parent's NOGC)

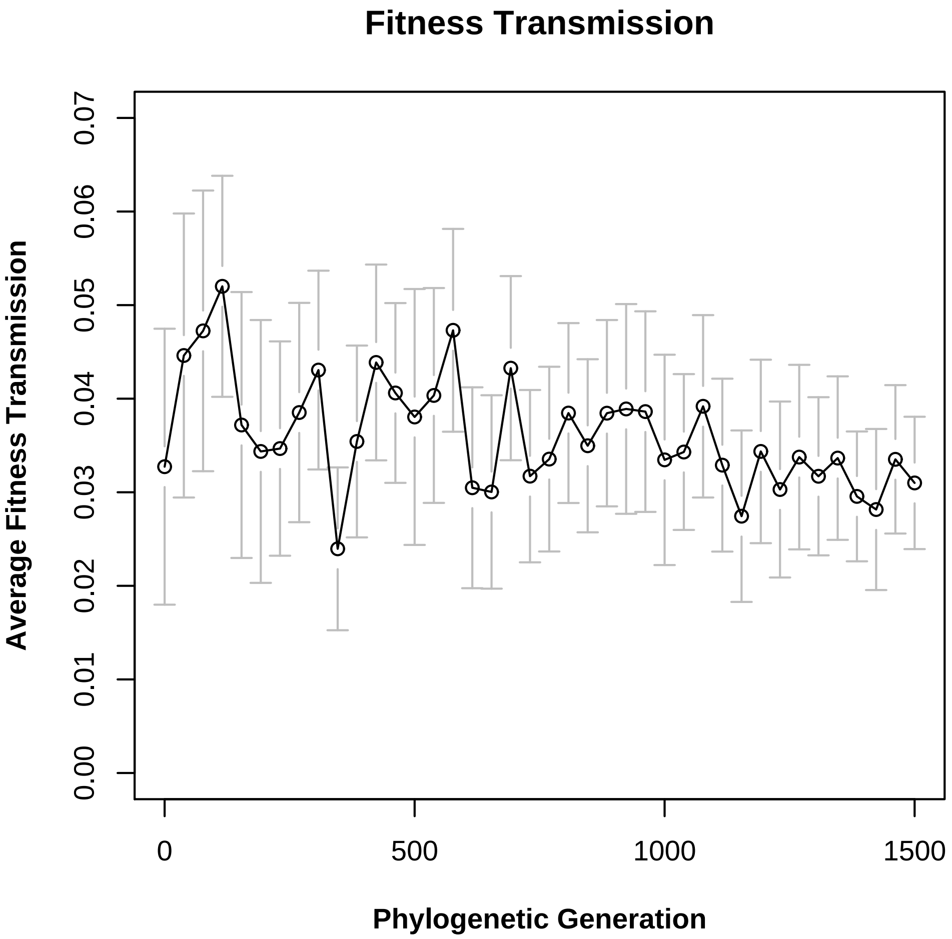

Figure 6.2: Fitness transmission measures the correlation between the fitness of individuals and their parent(s). The consistently positive values indicate the presence of non-random selective pressures.

can lead to undesired consequences if offspring is not uniformly distributed among the descendants. However, as pointed out in the original paper, the need for this normalization can be avoided if we use the NOGC of the *grandparent* instead of the NOGC of the parent. The precise algorithm and discussion of the measure can be found in (Miconi 2008b).

The fitness transmission values in figure 6.2 show a consistently positive correlation, thus indicating the presence of non-random selective pressures. The data shown was collected from 100 runs sampled until a lineage reached phylogenetic generation (PG) 1500 (data taken from the experiments discussed in chapter 8).

6.4 Phenotypic Trends

The measures discussed so far indicate continuous adaptive evolutionary dynamics in the system. Due to the choice of components for the Bedau-Packard statistics, the evidence for evolutionary activity has been restricted to structural components of the agents' neural controllers. We can use a method similar to the shadowing technique to track the evolution of morphological properties of the evolved lineages. With respect to the dynamics of the evolutionary process, its potential sensitivity to parameter settings is a critical aspect. There are usually many parameters (e.g., mutation rates) which are set more or less arbitrarily by the experimenter. Consequently, changes that occur over the course of evolution might in fact be mainly due to the stochastic nature of the process rather than a result of actual selection pressures present in the system. For example, if an evolutionary tendency to accumulate a lot of sensors can be observed, this does not necessarily imply that this is a beneficial adaptation. It might simply be that the probability of adding a sensor is higher than the probability of removing one. In many cases, selective pressures might actively work against these purely stochastic dynamics, in other cases, especially in the absence of strong selective pressures, changes will tend to follow those dynamics. To investigate this matter, I have analysed some of the parameters which are important to the evolutionary development in my system and compared those trends against a neutral shadow which should follow the stochastic bias of the parameter settings. In order to get comparable data, 10 runs where agents had a PG of over 1500 and followed an active foraging strategy were selected. Data and results in this section are published in (Pichler and Cañamero 2007) and were obtained using an ealrier version of the model. As discussed in section 5.4.1 there are no qualitative differences between results obtained by the two versions of the model. The results differ only in the quantitative distribution of agent populations across behaviour strategies.

I tracked various aspects that impact the energy budget and functionality of the agents. To compare the development of these parameters, I sampled three different sets of agents. For all three sets I sampled 10 runs with 50 agents each. The values in the figures 6.3 and 6.4 show the means within a 95% confidence interval.

- *Set A:* First generation agents created by the random initialization process of the MEAM to illustrate the average starting point of evolution.
- *Set B:* Stochastic agents that were 'artificially' reproduced to generation 1500 without any selective pressures but with mutation enabled. These agents are not evolved but their properties result from the parameter settings in combination with the stochastic nature of the mutation operators.
- *Set C:* Evolved agents of PG 1500. As mentioned above, I only consider agents with similar strategies. All agents follow an active foraging strategy.

6.4.1 Body Properties

The two body properties *size* and *solidness* define the mass and capacity of an agent and have a high impact on its metabolic costs. Figure 6.3 shows the results for size and solidness for sets A, B, and C. Additionally it shows the resulting mass of the agents. The differences between sets A and B are not significant. Both, size and solidness, are uniformly distributed numbers $\in [0.1, 1)$. Because mutation operators increase and decrease their value with equal probability, in the absence of selection pressures the mean roughly remains at the initial value. However, set C significantly deviates from these means. Solidness is close to its theoretical minimum of 0.1 and size is also significantly below the initial mean. Therefore, selection pressures resulting from the metabolic constraints must be responsible for this development. As stated above, all agents in set C follow an active foraging strategy and the movement cost of an agent is proportional to its mass. One possible explanation is that if survival depends on movement in the absence of stimuli to search for energy, then low weight (and therefore low movement cost) is selected for. Agents with this strategy trade off mobility against capacity and have to rely on finding energy sources frequently. On the other hand, in agents that wait for the energy to come to them, usually high capacity is selected for at the cost of higher movement costs (see fig. 5.3).

6.4.2 Sensors and Actuators

Both sensors and effectors can be added by mutation operators during the course of evolution. Figure 6.4 shows the average number of sensors and effectors for the three different sets of agents. Initial agents (set A) start with approximately three

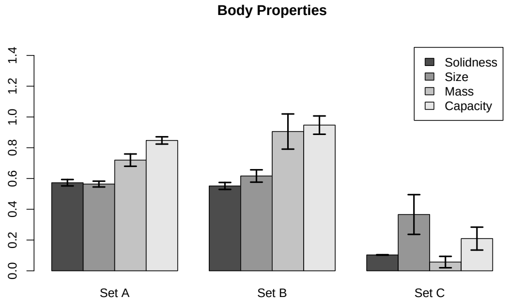

Figure 6.3: Development of the body properties solidness and size. Mass is defined by size and solidness and only shown to illustrate the impact of changes in these two parameters. Initial values (A) are uniformly distributed values from the interval $[0.1, 1)$. Mutation operators increase and decrease these values with equal probability so they do not significantly change without selection pressure (B). However, with selection pressure (C) a clear trend to reduce both size and solidness can be observed.

of each. After 1500 reproduction cycles without selection pressure, agents of set B average at about 6 effectors and 12 sensors. For the evolved agents (set C), the number of effectors does not significantly deviate from set B. However, the average number of sensors is less than two. This implies that in this case selection does not only influence the trend but actually reverses it to reduce the initial number of sensors against the strong stochastic trend to accumulate them. As components of the neural controller network, sensors and effectors have a small constant structural cost but a more likely explanation for the result shown in fig. 6.4 may be found in the variable metabolic costs for both components. Sensors are on the input side of the neural network and are activated by outside stimuli (or recurrent connections). This activation is likely to cascade through parts of the network and cause more costs. For example, we can imagine an agent that has a solidness sensor even though it has not evolved obstacle avoidance (in the 10 runs only two populations of set C

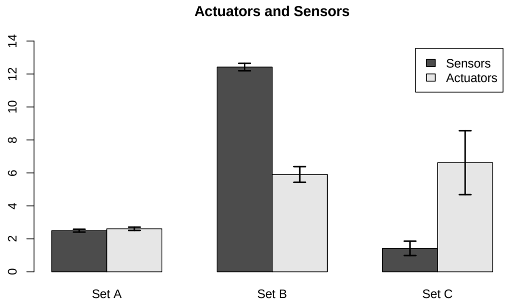

Figure 6.4: Evolutionary development of the distribution of sensors and actuators. The stochastic trend implies a large accumulation of sensors and a somewhat slower accumulation of actuators. The trend for sensors is reversed by selection pressures in the system.

did). The increased metabolic cost of sensing of the obstacle without a beneficial response makes a high risk situation (high probability of collision) even more costly. Thus, a sensor that does not benefit the agent can be very expensive.

Effectors, on the other hand, are on the output side of the network and if they have a positive threshold, they only get activation from upstream nodes of the network itself. The analysis of individual agents has shown that many of the effectors were never activated, some not even connected and can likely be considered evolutionary ‘garbage’. There does not seem to be enough selection pressure to remove unneeded effectors.

6.5 Discussion

The results reported so far give evidence to the claim that the system as implemented supports long-term, adaptive evolutionary dynamics. The data in the last section also suggests that selection favours particular morphological configurations for agents following an active foraging strategy. The evolutionary activity statistics and the fitness transmission measure both allow *quantitative* evaluation of the evolutionary dynamics. However, it would be desirable to get some qualitative evidence for the evolution of complex adaptive behaviour in the system. In chapter 5, I have outlined some examples of the *kind* of behavioural strategies that have been observed in various runs. With regard to the mechanisms underlying those behaviours, some of those strategies *seem* like reasonably 'complex' adaptations, as opposed to 'lucky coincidences' generated by the MEAM. The results contained within this section support the view that this is at least possible.

In the next section I will more closely inspect the complexity of the evolved behaviours and the mechanisms subserving them. The aim of the next chapter is to provide some evidence that the apparent complexity observed in the different strategies (discussed in chapter 5) can at least partly be related to complexity on a mechanistic level, and that this complexity has come about in a gradual accumulation of minor modifications, through continuous adaptive evolution by natural selection.

Chapter 7

Experiment III: Evolution of Neural and Behavioural Complexity

7.1 Introduction

Over the course of biological evolution, an increase in the complexity of the most complex organisms has occurred. This much seems uncontroversial if we compare the earliest forms of life with the most complex organisms of later stages in evolution. However, the exact reasons behind this *trend* for an increase in average complexity have been the topic of much debate (see e.g., (Sterelny 2001) for a summary of the debates between Dawkins and Gould, or (Miconi 2008a) for an extensive general review of different positions).

As suggested in (Miconi 2008a), much of the debate is based on ambiguous definitions of the terms ‘complexity’ and ‘trend’. In the case of a trend, the main question is whether such a trend towards greater complexity is an active (*globally pervasive* and *driven*) or a passive (McShea 1994, 1996) trend and, either way, to what extent natural selection is responsible by actively favouring increased complexity. Or if, as for example Gould (1989) argued, the observed trend in average complexity could be entirely passive (globally). A passive trend can lead to increased average complexity simply because life started out at a lower bound for complexity. Because nothing prevents more complex organisms from evolving from less complex ones, evolution will sometimes generate lineages that increase in complexity over time. Therefore, if life originated at this lower bound, mechanisms blind to complexity are sufficient for an average increase in complexity.

On closer inspection, it seems that most biologists agree (see (Miconi 2008a)) that there is no reason for natural selection to invariably select for increased complexity. Most certainly, complexity is no unequivocal indicator of evolutionary progress or success. Dawkins considers complexity a 'red herring' (Sterelny 2001), and therefore unsuitable as a measure of evolutionary progress. In his view, evolution is progressive in the sense that lineages become locally *better adapted* to their niches over evolutionary time. The process of local adaptation might or might not include an increase in complexity.

The core of this debate exemplifies the differences in motivation in Alife (see section 2.5). For evolutionary biology and Alife as theoretical biology, the question of whether such trends are active or passive is a fundamental theoretical question about the nature of evolution on earth. For the engineer attempting to build a system capable of evolving complex behaviour the situation is somewhat different. Unlike nature, she might try to actively seek the solution to a problem and be in a situation where she can reasonably assume that solving that problem requires at

least a certain amount of behavioural complexity. Therefore, to her, the crucial fact is that natural selection *has* indeed built such systems in nature, and the major task is to identify the necessary conditions under which this occurs.
It is simple enough to imagine an artificial system where natural selection does not lead to any appreciable increases in complexity, or even circumstances where it actively selects against it. Therefore, in the absence of an objective function to indicate change effected by artificial evolution, measures of complexity might give valuable insights into the nature of the observed process as long as they can be related to the observed behaviour.

In my model, the MEAM (see section 4.5) creates randomly configured seed agents without any predetermined functionality. Because of their small and random configurations, most of these agents fail to reproduce. Even the ones that eventually do are likely located close to the lower bound of complexity which still allows survival. Consequently, if there is any adaptive evolution going on in the system, it is not unreasonable to expect complexity to increase at least initially in some lineages (because that is what the system was designed for). As discussed above, this would lead to an increase in average complexity, irrespective of whether this trend was passive or driven.

7.2 Neural Complexity and Integration

Two of the main principles of structural and functional organisation in the brains of higher vertebrates are *segregation* and *integration*. Segregation refers to specialised groups of neurons or brain areas that selectively respond to certain input features. Integration, on the other hand, refers to the global integration of information from multiple specialised areas that occurs during perception and behaviour (Sporns 2002).

Based on these observations, Tononi et al. (1994) developed a measure of *neural complexity* which captures the interplay between these two aspects of neural systems and quantifies to what extent they integrate specialised information. Defined this way, neural complexity is high if a system contains specialised elements capable of system-wide interactions, and is low for random systems, or systems that are highly uniform (Sporns 2002).

Another benefit of these measures is that they are not solely based on the structure of the evolved neural networks but also can be made to take into account their dynamics observed during simulation runs. This renders the possibility to relate the complexity of the *underlying mechanism* to the complexity of the *observed behaviour* of specific lineages more likely. Without this link, the measure would be of no use in assessing behavioural complexity. On the other hand, if such a connection could be established this would allow some quantitative evaluations of adaptive evolution. For example, it would be possible to evaluate whether complex behaviour patterns were really acquired through adaptive evolution or simply the unlikely result of the seeding process. Additionally, the measure could be used to test the system under varying conditions and assess the impact of those changes on evolved behavioural complexity.

Both these questions will be discussed in the following sections. After a brief overview of the complexity measure, I will first assess to what extent neural complexity relates to observed behavioural complexity in specific lineages of agents and then consider global trends averaged over a number of runs.

7.2.1 Method

The measures for neural complexity and integration I apply in the following section are based on information theory and were originally developed to assess the dynamics of neuroanatomical motifs in the cerebral cortex (Sporns, Tononi and Edelman 2000, Tononi et al. 1994). With slight modifications, these measures have previously been applied to models of artificial evolution to investigate the influence of environmental complexity on behavioural complexity (Seth and Edelman 2004) and evolutionary trends in complexity in *PolyWorld* (Yaeger et al. 2008, Yaeger and Sporns 2006). Unlike other measures, these take into account structural and dynamical properties of the analysed networks.

In information theory (Cover and Thomas 1991, Shannon 1948), the uncertainty of a random variable X is described by its *entropy* $H(X)$:

$$H(X) = -\sum_{x \in X} p(x) \log p(x) \tag{7.1}$$

where $p(x)$ is the probability mass function of X. If the logarithm is to the base 2 the entropy is expressed in *bits*. Entropy describes the number of bits on average required required to specify the oucome of a random variable.

Every node in the neural network can be viewed as a random variable X. If the states of two nodes X and Y are independent, then the *joint entropy* represented by them is simply the sum of their individual entropies:

$$H(X,Y) = H(X) + H(Y) \tag{7.2}$$

However, because nodes can be connected, this is not necessarily the case as the state of one node can depend on the state of another. In this case, the joint entropy must be less than the sum of their individual entropies.

$$H(X,Y) \leq H(X) + H(Y) \tag{7.3}$$

This difference between the joint entropy and the sum of the individual entropies defines the *mutual information* (MI) of the two variables. Mutual information measures the correlation between two random variables.

$$MI(X:Y) = H(X) + H(Y) - H(X,Y) \tag{7.4}$$

In the case of a network consisting of multiple nodes, a multivariate extension of the mutual information between two variables can be defined. Thus, *integration* $I(\boldsymbol{X})$ (Tononi et al. 1994) quantifies the amount of statistical dependence between a set of variables $\boldsymbol{X}$ (the neural system consisting of all nodes X_i):

$$I(\boldsymbol{X}) = \sum_{i=1}^{N} H(X_i) - H(\boldsymbol{X}) \tag{7.5}$$

Neural complexity $C(\boldsymbol{X})$ is defined as the balance between segregation (local specialisation) and (global) integration or, more formally: “a neurally complex system is one in which small subsets of the system show high statistical independence, but large subsets show low statistical independence" (Seth and Edelman 2004). The corresponding measure thus captures the degree to which the network integrates specialized information (Sporns 2002) and is given by:

$$C(\boldsymbol{X}) = H(\boldsymbol{X}) - \sum_{i=1}^{N} H\left(X_i | \boldsymbol{X} - X_i\right) \tag{7.6}$$

Similarly to what (Seth and Edelman 2004) call *interactive* complexity, the joint entropy $H(\boldsymbol{X})$ of the system $\boldsymbol{X}$ is approximated by recording actual neural activity during the life time of the agents. To obtain better estimates, only agents with a life time of more than 1000 time steps were considered.

7.3 Experimental Setup

All data were collected from 50 identical (except for the random seed) simulation runs. The environment contained 50 energy sources and 50 obstacles uniformly distributed across a toroidal 200 by 200 (arbitrary units) square arena. Data collection was started as soon as a lineage reached phylogenetic generation (PG) 50. Agents were then sampled at intervals of 50 PGs until the lineage reached PG 2000. PG 2000 was picked as the termination criterion because experience with the system suggests that this typically represents about double the generation number required on average for populations to reach a state where no novel behaviours can be identified by visual inspection. The network activation data were recorded over the full life time of each agent with a PG divisible by 50. Node activation was discretized to three bit values. To reduce variance resulting from noise through seed agents or agents of different lineages, only one lineage per run was tracked.

The phylogenetic generation number was chosen over ‘time steps’ to determine the sampling intervals because it better represents evolutionary progression. Individual runs vary greatly in the number of time steps until a sustained population is established. Additionally, different populations have different time spans for the alternation of generations, depending on parameters such as average life span and reproductive activity. On average, the 2000 PGs simulated for each lineage translate to about 90 million time steps and approximately two million generated agents per run.

7.4 Results: Relating Neural Complexity to Behavioural Complexity

For the usefulness of the described measures with respect to the evolution of complex adaptive behaviour, it is important that the values for neural complexity and integration somehow relate to the observed complexity of behaviour. Watching different agents move through the environment, an observer naturally judges the displayed behaviour on a subjective scale of complexity. The behaviour of agents that evenly move through the environment with little observable response to external stimuli appears less complex than the behaviour of agents that evade obstacles and actively pursue a moving energy source. However, this intuitive perception of complexity is by definition very subjective and depends to a large extent on the knowledge the observer has about the environment, the agents, and the relationships between the two. As both Simon (1996) and Braitenberg (1984) have pointed out, given rich environments, the agent-side mechanisms underlying complex observed behaviour can be surprisingly simple.

However, with access to information about the components and rules defining the system, it is unlikely that one's intuitions about behavioural complexity should be completely unrelated to a formal measure that effectively captures structural and dynamical aspects of neural complexity. To determine to what extent this is true, it is necessary to observe concrete simulation runs and establish if changes in observable behaviour are correlated with changes in neural complexity. If the two even broadly agree, the measure would be an extremely powerful tool to automatically identify runs with high behavioural complexity.

Figure 7.1 shows the average complexity scores of four different lineages evolved under identical conditions (except for the random seed). The top two figures (7.1 (a) and (b)) show an overall increase in complexity, where phases of a relatively steep increase are followed by phases of a slight decrease. Visual observation of the behaviour of agents before the increase in complexity (around PG 300 in both runs), and then again at the time of the following peak (around PG 800), confirms that the former do not avoid obstacles while the latter do. Analyzing the networks reveals that in this period 'obstacle sensors' were added, followed by additional neurons and locomotive effectors. After the initial peak follows a slight decrease in complexity. The reasons for this have not rigorously been investigated but I would assume that this is likely due to a consolidation phase where the mechanism underlying the novel behaviour is optimized. Similarly, the following increases (around PG 1400 and PG 1200 respectively) correspond to the appearance of active foraging behaviour.

On the other hand, the networks in the third run displayed in fig. 7.1 (c) show no real increase in complexity over time and an overall lower complexity score. Visual observation of agents of this lineage over time confirms that they have only evolved a rather frugal form of obstacle avoidance and do not actively approach energy sources. Many lineages exhibiting simple behaviour strategies show a significant decrease in complexity over evolutionary time. Again, the formal measure and the intuitive assessment are in good agreement.

Even though the picture is not quite as explicit for each of the 50 runs, two observations hold across all runs: high intuitive behavioural complexity is generally reflected in a comparatively high neural complexity. This observation is consistent with the results reported in (Seth and Edelman 2004), where the same measures were applied to networks evolved for a target fixation task. Secondly, lineages with very low neural complexity never exhibit complex behaviour (e.g., active foraging). This result is equally important if the measure is to be of any use in relating the two forms of complexity.

So far, the match between the two assessments looks very convincing. Considering the implementation of the measure, however, it is not entirely surprising that the reverse of the two above observations is not generally true. An increase in neural complexity *does not* necessarily correspond to subjectively complex behaviour. The last run shown in fig. 7.1 (d) features a very steep increase in neural complexity, ultimately resulting in the highest complexity observed across all runs. Yet, the agents of this lineage exhibit no obstacle avoidance, foraging behaviour or other complex behavioural features. The high complexity scores solely result from large oscillations in the neural structure underlying their base movement. The conclusion that high values of neural complexity do not necessarily correspond to complex or

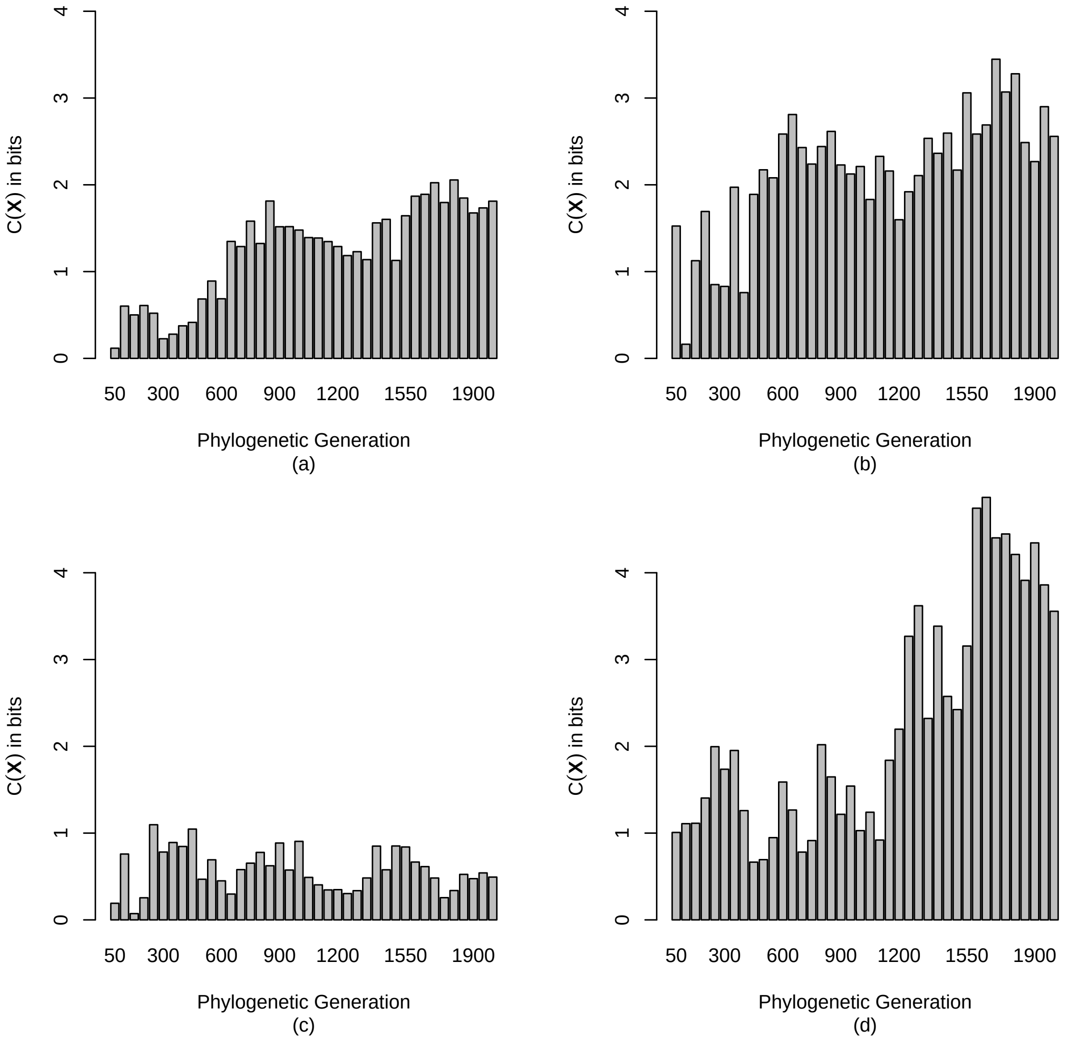

Figure 7.1: Evolution of complexity scores for four different lineages. Figures (a) and (b) show a step-like increase in complexity which relates to the appearance of new behaviours. Figure (c) shows no significant increase in complexity over evolutionary time. Figure (d) shows a steep increase in complexity which is not accompanied by complex changes in observed behaviour.

even adaptive[1] behaviours is consistent with results reported in (Yaeger et al. 2008),

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[1] Even though in this case this oscillation in locomotive effector activation is adaptive because more energy is saved than momentum is lost.

where simply maximizing neural complexity did not lead to adaptively useful or complex behaviour.

7.5 Results: General Trends in Neural Complexity and Integration

As stated above, the basic assumption is that a trend towards increased complexity would not necessarily be the result of a globally driven selection for increased complexity, but of the evolution of some lineages whose local adaptation process leads to an increase in complexity. Therefore, while we might expect a slow global trend towards increased average complexity across multiple runs (at least for some time), we would also expect individual lineages to reduce their complexity to adapt to a certain survival strategy.

Figures 7.2 and 7.3 illustrate the trends of integration $I(\boldsymbol{X})$ and neural complexity $C(\boldsymbol{X})$ averaged over 50 evolved lineages. Both, integration and complexity show clear and significant trends towards increased values across the whole measured evolutionary period. Normalized values were calculated to ascertain that the observed increases are not simply artifacts of larger neural networks sizes but reflect the proportion of actual information processing in the networks. It is worthwhile to compare these figures with the results reported in (Yaeger and Sporns 2006) where the same measures where used in a superficially similar system. They report no significant trend in integration and a “modest” trend towards increased complexity. However, a closer look at their results reveals that the significant part of this increase occurs exclusively during the GA-phase in the beginning of the run. After this, during the

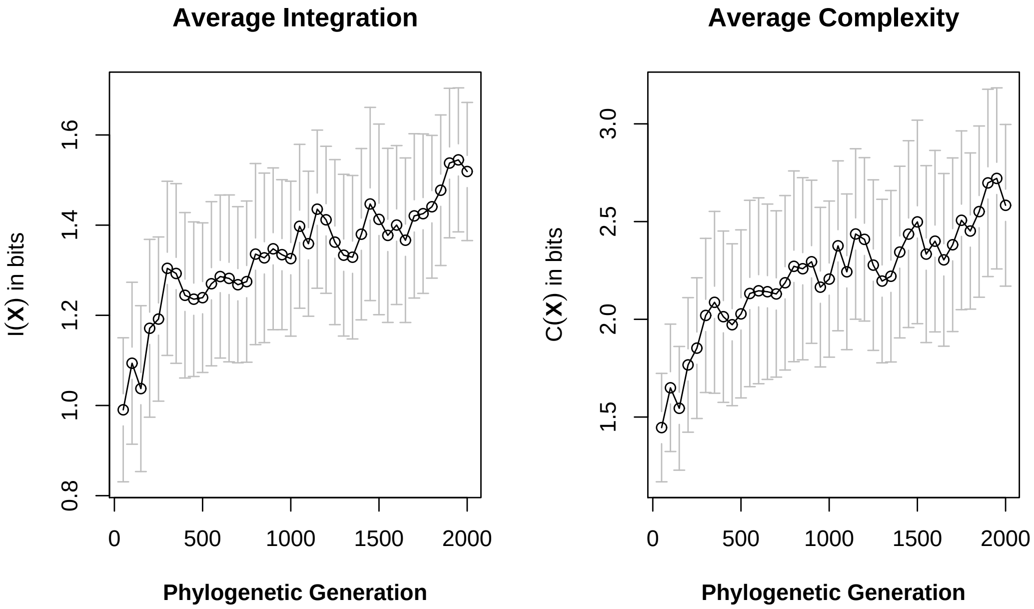

Figure 7.2: Evolution of neural integration (left) and complexity (right) averaged over 50 simulation runs. Both values show a significant increase over the observed period of 2000 phylogenetic generations. Error bars show the 95% confidence intervals.

stage of natural selection nothing much seems to happen. There are several possible reasons for these differences in result. Firstly, they use seed agents hand-crafted with “reasonable” (Yaeger and Sporns 2006), near-viable behaviour strategies and a fitness-based, steady-state genetic algorithm to generate viable populations (for about a third of the measured period). It is possible that this combination might bias the system towards a certain configuration which later does not provide a further gradient for natural selection. Secondly, the time they permit their system to evolve seems surprisingly short on an evolutionary scale. Unfortunately, they do not provide figures on how many generations their experiments involved but considering the reported average life spans of 500 time steps, simulating only 10000 time steps

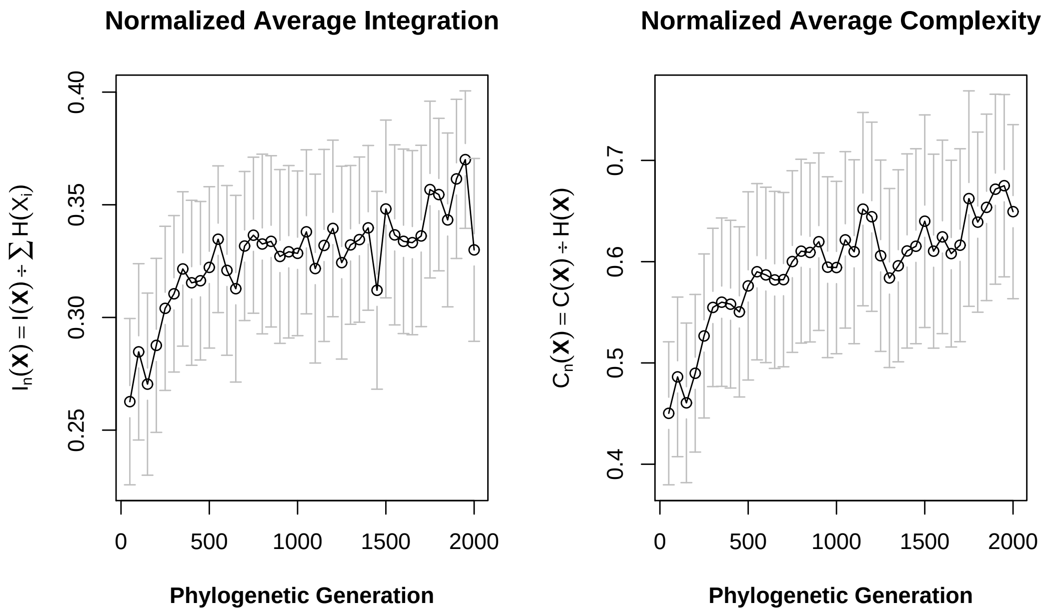

Figure 7.3: Normalized neural integration (left) and normalized complexity (right) averaged over 50 simulation runs. The increase in the normalized values suggests that a larger proportion of the information processing is done in a coherent way as opposed to just being an artifact of increased network size. Error bars show the 95% confidence intervals.

(Yaeger and Sporns 2006) might not be sufficient to capture lasting evolutionary trends. In any case, the fact that complexity increases only during the GA-phase weakens any conclusions about its possible causes. It is unclear whether the increase is the result of adaptive evolution or simply caused by the artificial selection mechanism replacing unsuccessful seed agents with successful ones.

To avoid these ambiguities and to ensure that changes were more likely effected by adaptive evolution, the results shown in figures 7.2 and 7.3 capture a much longer period[2] of evolutionary activity, data collection was performed on a single lineage

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[2] The observed 2000 phylogenetic generations are, of course, still minuscule compared to the time scales of natural evolution. However, as shown in the presented results, the time period was

per run, and sampling was only started after that lineage had reached PG 50.

In combination with the findings on sustained evolutionary activity reported in chapter 6, the trend towards increased complexity which can, at least partly, be explained by increased behavioural complexity suggests that the present system exhibits continuously adaptive evolutionary dynamics and is capable of generating behaviour of (at least to some extent) increasing complexity.

7.6 Discussion

Pulling together the observations from chapter 5, where I discussed examples of qualitatively distinct behaviour strategies observable in the system, chapter 6, where I showed that evolutionary activity is unbounded for the observed simulation period, and the results presented in this chapter allows to draw a more complete picture to lend support to my main conclusion.

Firstly, the system I presented in chapter 4 is only the second system after Channon's *Geb* (Channon 2001b) to exhibit unbounded evolution according to the Bedau and Packard statistics of evolutionary activity (Bedau et al. 1992). Unlike *Geb*, however, my system was explicitly designed to offer increased 'behavioural transparency' (Channon 2001a) to allow a qualitative assessment of evolutionary products over evolutionary time. The importance of behavioural transparency in a system aimed at open-ended evolution was recognised by both Channon (2001a) and Taylor (1999) because the huge amount of data produced over evolutionary time and across evolutionary runs makes it difficult or impossible to rigorously analyse and understand

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long enough to show distinct events of adaptive evolution.

each evolved product at the mechanistic level. Without behavioural transparency, it is therefore extremely difficult to understand what exactly is happening in the system over evolutionary time. The ability to identify and understand qualitatively novel behaviours, on the other hand, allows one to trace the evolutionary process by observing populations at different stages of a simulation run. For example if obstacle avoidance behaviour is at some point present in a lineage, where earlier this behaviour did not exist.

In the absence of an external objective function against which agent populations can be measured, other sources of information about the temporal evolution of the system are crucial. Even the trivial sounding conclusion that the evolutionary products observed at a given time are, in fact, products of gradual evolution as opposed to simply being ‘freak accidents’ of the seeding process can only be supported if it is possible to understand the temporal evolution of the system. Visual observation, of course, can only be used as a first indicator of what is happening as it allows mainly qualitative observations which, to some degree, are necessarily subjective. For this reason, it is necessary to find reliable and useful metrics that allow quantitative assessments of the nature of the evolutionary progression of evolving lineages.

The measures of neural complexity and integration discussed in this chapter were shown to be partly useful for this purpose as they successfully capture certain aspects of the evolution of the agent populations over time. Most importantly, the emergence of qualitatively novel behaviours could usually be identified by a corresponding wave-like increase in neural complexity.

Even though the complexity (however measured) of a particular lineage does not necessarily increase over time in a system exhibiting open-ended evolution, most definitions of open-ended evolution require the system to have the *capability* to generate open-ended complexity (Nehaniv 2000b). As discussed in the introduction to this chapter, if an evolutionary process starts out at the lower bound of complexity and nothing prevents the system from generating lineages of increasing complexity, the average complexity (across all lineages) can be expected to increase over time. Simulations were run for twice the time it approximately takes for average populations to reach a state were no novel behaviours can be identified by visual inspection. The measured average neural complexity, however, continued to increase for the whole simulated period. There are two possible explanations for this: firstly, neural complexity increases due to structural parameter settings in the system (e.g., mutation rates) despite the high metabolic costs of perception, neural processing, and action which, other things being equal, should favour simple neural organisations. Secondly, which, to me, seems more likely, the metaphor which allows easy interpretation might break down once all behaviours that can readily be identified (e.g., obstacle avoidance, active foraging) are present in a lineage. As briefly mentioned in chapter 5, it has turned out to be extremely difficult to interpret or classify the ecological interactions between agent populations. Thus, it might be the case that the increase in neural complexity is adaptive but that the system proves as difficult to visual interpretation at the ecological level as Channon (2001a) and Taylor (1999) found theirs to be at the individual level.

In conclusion, the results presented in the previous three chapters support my claim that the presented system improves upon previous systems in that, on the one hand, the gradual evolution of novel behaviours can be observed and interpreted (Channon 2001a, Taylor 1999) qualitatively and, on the other hand, unlike in (Yaeger and Sporns 2006), the quantitative assessment of neural complexity shows a steady increase in average neural complexity for the full simulated period which was orders of magnitudes larger than the one simulated for *Polyworld* (10^4 time steps vs. $\sim 10^8$ time steps).

Finally, it has to be stressed at the end of this discussion that, as with unbounded evolutionary activity, unbounded average (neural) complexity in a system exhibiting open-ended evolution is about necessity, not sufficiency. This makes intuitive sense, and in the case of neural complexity was also shown by Yaeger et al. (2008), where simply maximizing neural complexity did not lead to adaptively useful or complex behaviour. Also, it is important to resist the temptation to think of either neural complexity or observed behavioural complexity as some form of absolute 'performance' indicators. Experiments (results not shown) where two populations were transferred into a shared environment have always resulted in one lineage eventually outcompeting the other (leading to their extinction). However, neither neural complexity nor intuitive sophistication of behaviour were a significant predictor of success. If anything, the 'simpler' lineages seemed to do slightly better. This is not surprising as fitness is a local criterion (e.g., in time and space) and this observation is also not at odds with intuitive notions of complexity. Highly specialized animals with a sophisticated behaviour repertoire are more susceptible to environmental change than very simple organisms (Begon et al. 2006).

Chapter 8

Experiment IV: Effects on Diversity in Evolved Behaviour Strategies

8.1 Introduction

The main argument for building an artificial evolution system based on natural selection instead of using traditional methods of evolutionary computation is that the former does not require the definition of an explicit fitness function as natural selection is an emergent property of the modelled system dynamics. The dynamic fitness landscape generated by local interactions and competition between populations of agents in an environment allows more 'creative' (Ray 1991b) and more enduring adaptive evolutionary dynamics (Channon and Damper 1998a, Packard 1989, Ray 1991b, Yaeger 1994).

A similar point can be made for reproduction (Taylor 1999). In many artificial evolution systems (including the one discussed in this thesis), unlike in biological evolution, self-reproduction is not an emergent, self-organized property of the physics (Kauffman 1993) of the system. Instead, an explicit mechanism is applied at the ‘algorithmic’ level of the system which defines the condition under which agents are reproduced. Algorithmic level means that this mechanism, like an artificial selection mechanism, is not an emergent property of the system dynamics but a design choice external to the evolutionary system itself. Previous experiments (Nehaniv 2002) have demonstrated that the mode of reproduction can constrain and affect evolution of ecological niches in a *Tierra*-like system.

This chapter describes the results of a series of experiments performed to assess how the choice of reproductive mechanism impacts the evolutionary dynamics of the system. In particular, the experiments aimed at identifying the influence of this mechanism regarding the available evolutionary pathways to evolve different successful behaviour strategies.

Additionally, in the second part of this chapter, the impact of the reproductive mechanism is contrasted with the effect of changes on another level of the system, namely that of different resource and obstacle densities and ratios in the environment.

8.2 Experiments IVa: Reproductive Mechanism and Diversity of Behaviour

Reproduction strategies—or how an organism manages the trade-off between individual survival and reproductive success—are one of the sources of niche creation and diversity in nature (Begon et al. 2006). This trade-off expresses to what extent an organism invests acquired resources into individual survival (or self-maintenance) or into creating offspring (reproduction). The ability to influence this relationship requires a decoupling of individual survival and reproductive success. This issue of *progeny vs. persistence* trade-offs was also investigated from an information theoretic perspective in (Polani, Nehaniv, Martinetz and Kim 2006). If reproduction is not an emergent property of the system dynamics, in other words, if the agents are not truly self-producing (Taylor 1999), the system must contain a mechanism ‘external’ to the laws of the virtual world which handles the multiplication of agents if some condition is met. It is argued here that this choice of reproductive mechanism can either allow the evolutionary process to explore this trade-off or constrain it by equating individual success with reproductive success.

The reproductive mechanism described in section 4.4.3 was designed with this trade-off in mind. The hypothesis is that the decoupling of individual survival from reproductive success increases the number of possible evolutionary trajectories, i.e. allows more diverse successful strategies to evolve. In order to assess the impact of this choice of mechanism, two additional mechanisms were implemented to allow a comparison of the resulting evolutionary dynamics. The reproductive costs ψ are given in equation (4.8) in section 4.4.3. The two additional reproductive mechanisms were:

8.2.1 Energy Threshold

As the first mechanism, we use a fairly straightforward energy threshold as was used, for example, in (Bedau et al. 1992, Fletcher, Zwick and Bedau 1996) and (Menczer and Belew 1996b). Whenever the life energy of an agent exceeds a specified threshold, the agent reproduces. Therefore, in this condition agents can collect more energy than their capacity c and reproduce if their life energy $l \geq c + \psi$. After reproduction, the reproductive costs ψ are subtracted from their life energy.

8.2.2 Life Time

The second mechanism is slightly more indirect and depends on the life time of the agents. In this condition agents reproduce periodically after a specified number of time steps. To integrate the mechanism into our framework and make it comparable to the other two conditions, the period length should reflect the reproductive costs for the agent architecture in question. To achieve this, the period length p for a given agent is $p = \frac{\psi}{\kappa} + 1$, i.e. the number of time steps after which the constant metabolic costs κ exceed the reproductive costs. Thus, the longer an individual survives, the more offspring it creates.

In both cases, reproductive success is directly coupled to the ability to find and consume the energy resource. In the case of the energy threshold, maximizing energy intake will automatically maximize reproductive success. In the time condition, maximizing life time will theoretically lead to the greatest reproductive success.

Finally, the third mechanism (*Depot*) is the mechanism introduced in section 4.4.3. The three mechanisms under consideration differ in how reproductive success is linked to the energy resource. In the first two cases, the ability to find and consume the energy resource and survive is directly coupled to reproductive success. In the last case, these two aspects are decoupled and thereby might allow natural selection to explore more diverse survival strategies. The results show that the biases introduced by this choice have significant implications for the whole dynamics and outcome of the simulated evolution.

8.2.3 Experimental Setup

To study the impact of the reproductive mechanism on the evolved morphologies and behaviour strategies, 100 trials for each of the three mechanisms were run. This allows to assess this influence under otherwise identical conditions in the same simulation environment. Apart from the reproductive mechanism, all experimental trials were identical save for the random seed; random numbers are used to generate initial agents created by the MEAM and for all mutation operators. All 300 individual trials were run until a lineage reached *phylogenetic generation* (PG) 1500. At this point I took a snapshot of the simulation environment and recorded a number of properties relating to population and environment. Additionally, I sampled the population and calculated the averages over certain morphological properties of the agents of the same lineage present at the time of sampling.

I test the hypothesis that the depot mechanism permits to generate a larger variety of morphologies and survival strategies because reproductive success is decoupled from individual survival. This should grant the agents more freedom over when and how they invest energy in offspring. As discussed in chapter 5, this mechanism is indeed capable of evolving very different viable strategies.

It is important to clarify what I mean by diversity. In ecology, diversity usually refers to the number of species and their relative abundance in a certain habitat or area under investigation. This poses two problems; the concept of ‘species’ itself is the subject of much debate in biology (see e.g., (Hey 2001)), and it is even more vague in artificial systems. A simple definition given in many biology textbooks (e.g., (Campbell and Reece 2008)) follows Mayr who defined a species as the members of a natural population of organisms which interbreed in the wild and produce viable offspring (de Queiroz 2005). Because reproduction in my system is asexual, this definition is not applicable. To further complicate matters, what we are concerned with here are not actually different 'species' evolved in the same habitat, but different populations of agents evolved under the same conditions. Most individual runs produce very homogeneous populations where all agents are ultimately descendants of the same 'founding' agent. This means that, as far as the biological concept of species is concerned, there was little diversity within a single run. The type of diversity I take into account instead is the variation of evolved morphologies and strategies across *different* runs performed under the same conditions.

In other words, I 'replay the tape' (Gould 1989) of evolution 100 times and observe to what extent the outcomes differ. In this way, diversity can be viewed as variation in viable populations for a given set of constraints. In more computational terms, I investigate how the fitness landscape varies under different conditions to either lead to convergent evolution of similar agents, or allow a number of significantly different viable strategies in repeated runs. In the case where all runs converge to similar solutions, the implication would be either that the fitness landscape has only one maximum or that constraints in the dynamics prevent the system from reaching alternatives. On the other hand, if individual runs converge on a variety of different solutions, the fitness landscape has several local optima, and the dynamical constraints allow for a broader exploration of the 'solution space'.

Table 8.1: Properties of the population and morphologies used for classifying the evolved diversity.

Population properties	
Life time	Average age of agents in time steps
Population size	Number of agents at sampling point
Offspring	Average number of offspring per agent
Environment energy	Residual energy in environment
Agent energy	Energy stored in agents
Morphological properties	
Solidness	average solidness of agents
Size	average body size
Neurons	Average number of neurons
Synapses	Average number of synapses
Sensors	Average number of sensors
Effectors	Average number of effectors

8.3 Results: *Depot* Mechanism Generates Most Diversity

With the snapshot data from all 300 runs, two matrices were obtained where columns represent the morphological and population properties, respectively, and each row holds the sampled values for one run. All data analysis was done using *R* (R Development Core Team 2007) and the *cluster* package (Maechler, Rousseeuw, Struyf and Hubert 2005) for cluster analysis. The recorded properties of the population and morphologies are given in table 8.1.

To ensure that non-random selection occurred under all three conditions, fitness transmission (Miconi 2008b) (see section 6.3) was measured over the whole simulation period. Figure 8.1 shows the average fitness transmission for all three mechanisms and confirms that non-random selection pressures were indeed present. Therefore, it is possible to analyse whether the different reproductive mechanisms had any

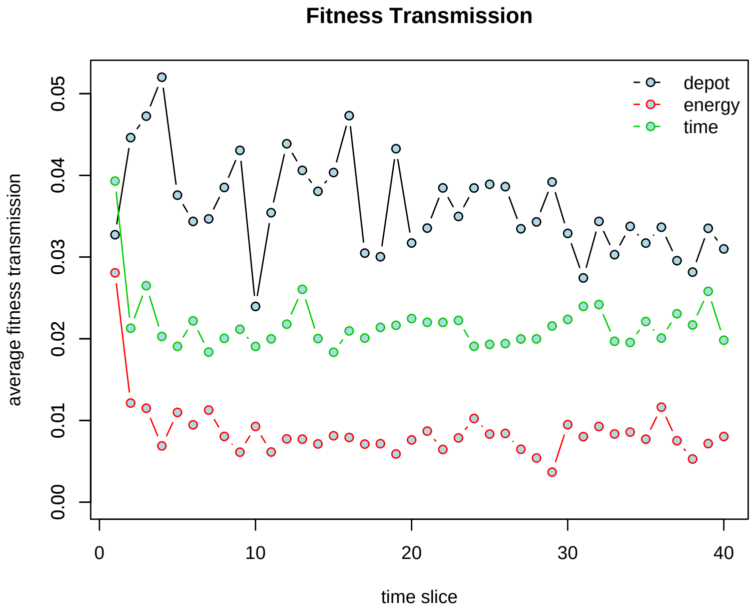

Figure 8.1: Fitness transmission for all three experimental conditions. The consistently positive values indicate the presence of a non-random selection process.

significant impact on the diversity of evolved survival strategies.

From the discussion of different behaviour strategies in chapter 5 it is clear that, to a large extent, the morphological properties of an agent reflect its behavioural strategy. This allows an approximate classification of behaviour strategy on the basis of morphological properties without the need to observe the behaviours occurring in every single one of the 300 runs. Most strategies can be classified by the presence or absence of three general behavioural patterns: agents respond to the presence of energy (e.g., by slowing down), agents try to actively approach energy, and agents try to avoid obstacles. The main overall behaviour strategies resulting from this categorization (discussed in more detail in chapter 5) are summarized as follows:

- *Drifters* do not actively approach energy sources or avoid obstacles. They 'drift' through the environment with one locomotive effector; either they slow down if they accidentally move over an energy source or they do not react at all. Drifter agents are smallest, have lowest solidness and small neural networks. Their populations are large and their average life spans short.
- *Foragers* actively approach energy sources but do not avoid obstacles. They are slightly larger than drifters and have larger neural networks. Their population size is smaller and their life spans are longer than those of drifter populations.
- *Avoiders* do not actively approach energy sources but try to avoid obstacles; they have higher solidness than either of the previous agents and neural networks similar in size to foragers.
- *Allrounders* actively approach energy sources and try to avoid obstacles. They are similar in size to foragers and similar in solidness to avoiders. Allrounders have the smallest populations and the longest life spans.

8.3.1 Data Analysis

One way to obtain a visual representation of the hierarchical structure of the diversity of morphology is to use agglomerative nesting ($AGNES$), a hierarchical clustering method (Maechler et al. 2005). Figure 8.2 shows the dendrograms for each reproductive mechanism. The dendrograms indicate a grouping of morphologies into about four clusters for the depot condition. For the other two conditions the picture is less clear as most samples seem to lie in one big cluster.

A different way to classify the data is to use a k-means type clustering algorithm.

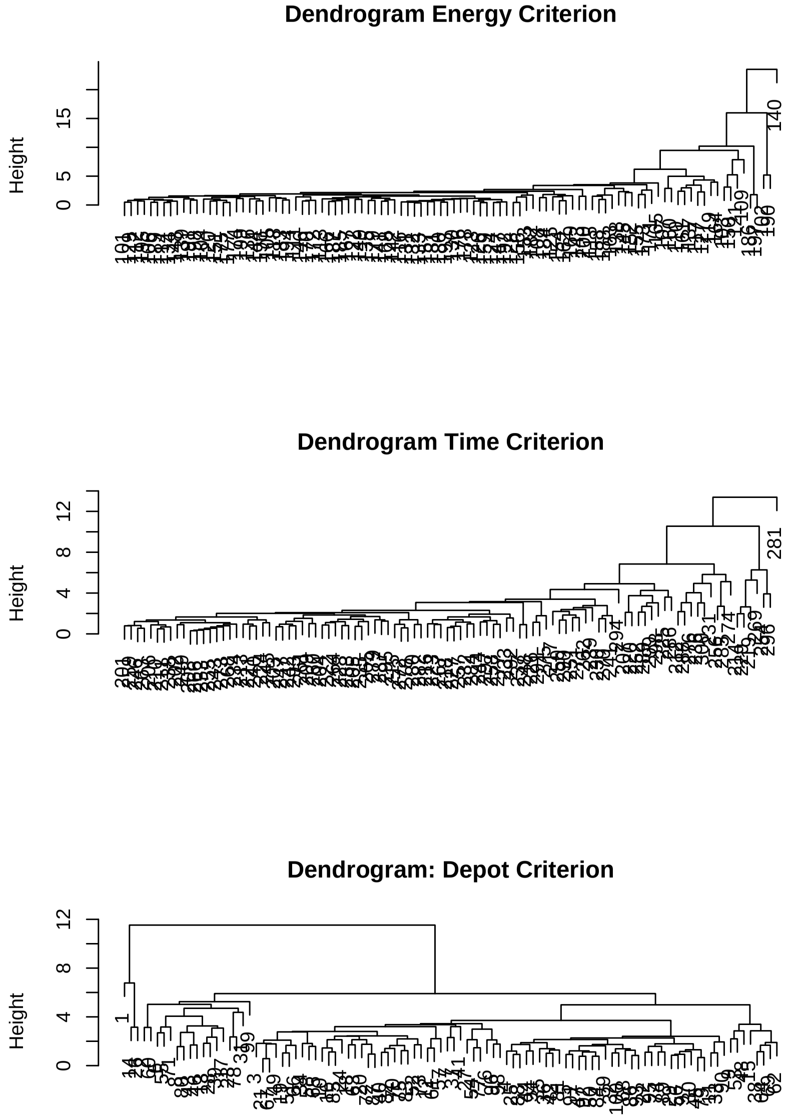

Figure 8.2: Figures show the dendrograms for the different reproductive criteria (100 runs each) using agglomerative nesting. Leaves represent data collected from individual runs (see table 8.1). The hierarchical clustering indicates more distinct clusters in the *depot* condition compared to the two control conditions.

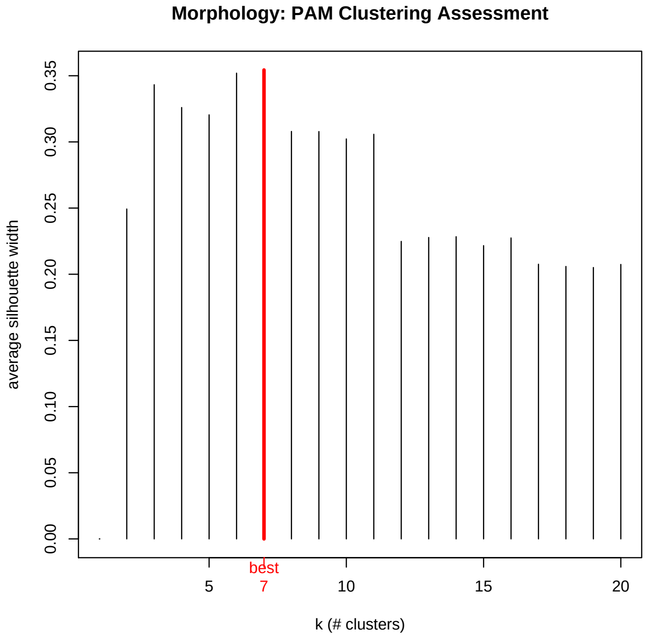

Figure 8.3: Average silhouette width to assess the quality of the clustering of morphological data using different values for the number of clusters k. The maximum silhouette width indicates the optimal number of clusters ($k = 7$).

The problem with such algorithms is that they typically require the desired number of clusters as an input parameter. From the dendrograms in figure 8.2 one could heuristically guess that we might need around 6 clusters to optimally classify the whole data. A more systematic way to determine the optimal number of clusters k for our data set is to use the *silhouette validation technique* (Rousseeuw 1987). Silhouette information is based on the comparison of the tightness and separation of a cluster. The average silhouette width for a given value of k gives an indication about the quality of the clustering; the k for which the average silhouette is maximal results in the optimal clustering. Figure 8.3 illustrates the average silhouette for different values of k and shows an optimal clustering for $k = 7$.

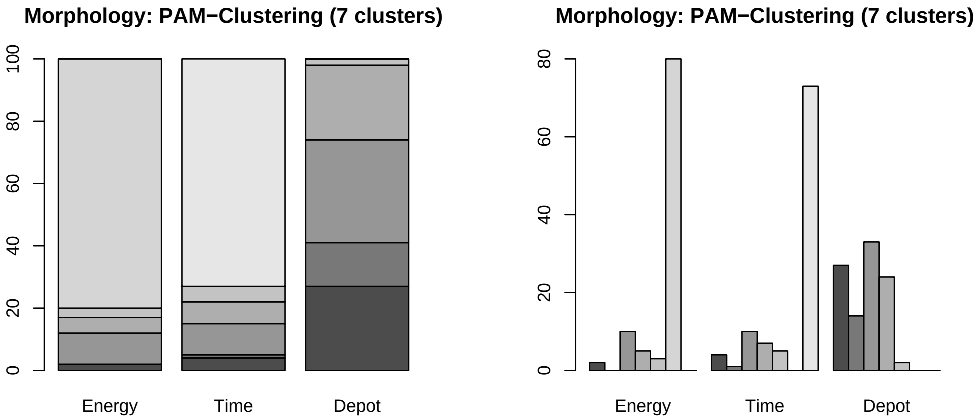

Figure 8.4: Figures show a stacked bar chart (left) and the histograms (right) of the distribution of morphological data of 100 evolved populations under each condition (depot, energy, time) clustered into 7 clusters. Clustering was obtained using *PAM* (partitioning around medoids) on 6 morphological properties (see table 8.1) using the standardized dissimilarity matrix. Diversity is highest for the depot mechanism.

Table 8.2: Measured diversity (entropy) for 7 clusters.

Reproductive condition	Entropy
Energy	1.070
Time	1.400
Depot	2.042

The diversity of evolved morphologies can thus be assessed by assigning each morphological sample to one of seven clusters. As a measure of diversity, the distribution of the samples from each reproductive mechanism across each cluster was used. Figure 8.4 shows a bar plot and the histograms for the three conditions. The diversity is measured as the *entropy* of the histograms (in ecology this is referred to as the *Shannon-Weaver index* (Krebs 1989)). The resulting entropies for the optimal clustering ($k = 7$) are listed in table 8.2; a graphical illustration is given in fig. 8.4.

The figures clearly indicate that the reproductive mechanism has a very significant impact on the evolved morphologies. Under otherwise identical conditions, the *depot* mechanism generates a greater diversity of different morphologies. In particular, the *energy* mechanism (which was the one used in both (Bedau et al. 1992) and (Menczer and Belew 1996b)) converges on very similar solutions in every run.

A closer look at the behaviour of the agents evolved using this mechanism reveals that they mostly follow the minimal *drifter* strategy described above and neither active foraging nor obstacle avoidance were observed in runs using this mechanism. However, because the entropy depends on the number of clusters used, one can also look at the entropies for different clusterings. Figure 8.5 shows that the diversity is persistently highest for the *depot* mechanism, irrespective of the number of clusters used. This is consistent not only with our hypothesis that decoupling individual from reproductive success creates a *persistence vs. progeny trade-off* (Polani et al. 2006), which gives the agents more autonomy to pursue different reproductive strategies, but also with what can be observed looking at examples of evolved populations. As stated above, agents evolved with the energy threshold mechanism followed the simplest viable strategy. Agents evolved with the *time* mechanism frequently evolved collision avoidance but active foraging wasn't observed. Only in the *depot* condition could agents regularly be observed which exhibited both obstacle avoidance and active foraging.

So far I have only discussed the impact of the different reproductive mechanisms on evolved morphologies. However, different survival strategies are also reflected in the properties of the evolved populations. With the clear trends in morphological diversity, we would expect to find the same trends in the collected population data, as these data are not independent. For example, the limited energy in the environment

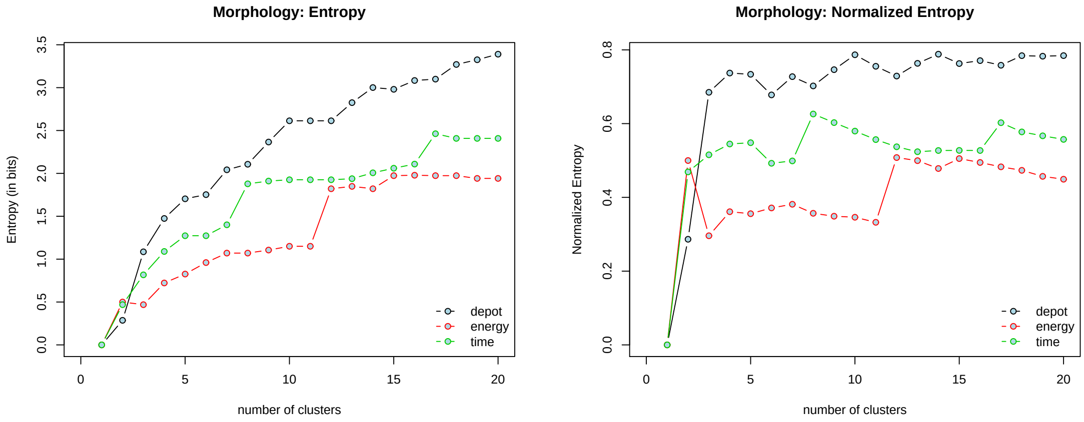

Figure 8.5: The diversity (entropy) depends on the number of clusters used. The two plots show raw entropy (left) and normalized entropy (right) of morphological data (see table 8.1) for an increasing number of clusters ($k \in [1..20]$). The graphs show that the diversity is persistently highest for the depot criterion irrespective of the number of clusters used.

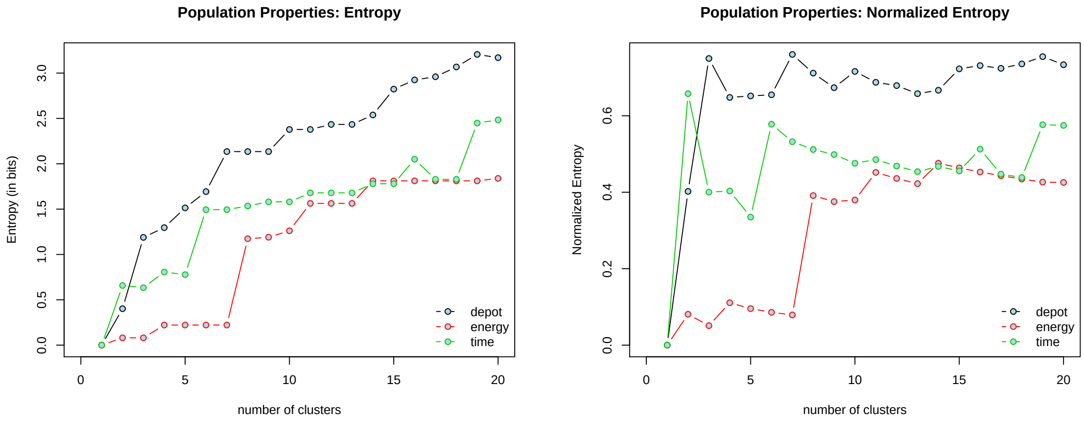

Figure 8.6: The two plots show raw entropy (left) and normalized entropy (right) of population properties (see table 8.1) for an increasing number of clusters ($k \in [1..20]$). The graphs show that the diversity is persistently highest for the depot criterion irrespective of the number of clusters used.

determines the carrying capacity for a certain population of agents. The environment will sustain smaller populations of big or more complex agents with higher metabolic consumption than of small and simple agents. Also, small agents with very simple survival strategies will typically have shorter life-spans than comparatively sophisticated agents with active foraging or obstacle avoidance. Figure 8.6 shows the entropy distribution over different clusterings. As expected, the diversity is again highest for the depot condition, and the overall trend is similar to the one observed in the analysis of the morphological data. This confirms our hypothesis that the choice of the reproductive mechanism has a significant impact on a wide range of observable parameters under direct (morphology) and indirect (population properties) evolutionary control.

8.4 Experiments IVb: Environmental Variation and Diversity of Behaviour

To put the results discussed in the last section into a greater context, it suggests itself to compare the scale of the impact of the choice of reproductive mechanism with that of other variation introduced into the system.

Because *adaptive evolution* means that populations adapt to their local environments, it is reasonable to explore the effect of different environmental configurations on the evolved populations. The impact of environmental variation and structure has been investigated in numerous contexts. For example, using their *LEE* (Menczer and Belew 1996b) model, Menczer and Belew have characterized how various modifications in environmental structure lead to different adaptations in the evolved populations (Menczer and Belew 1996a). They report that patchiness in resource distribution affects the efficiency of evolved foraging strategies and that in dynamic environments with seasonal fluctuations in resource availability, a division of agents into sub-populations exploiting different seasonal niches occurred.

The authors in (Todd and Yanco 1996) also studied the effects of varying different aspects of the environment like food distribution and resource regrowth rates and found a more intricate relationship than expected. They report that not only does the structure of the environment affect the evolved behaviour strategies, but that, in turn, the evolved strategies influence which aspects of the environment the populations adapt to.

The effect of environmental structure on evolutionary adaptation was also investigated in (Fletcher, Bedau and Zwick 1998, Fletcher et al. 1996). The authors found two factors were significant in determining adaptive success: the information content of the environment and the expected utility for optimal action. They conclude that adaptability was low if the agents had either too little or too much information about the pragmatic importance of local environmental conditions.

The following section describes the details of the experimental setup and summarizes the results of a set of experiments aimed at measuring the impact of different resource and obstacle densities on the diversity of evolved behaviour strategies.

8.4.1 Experimental Setup

The data discussed were obtained by simulating 30 runs (identical except for the random seed) in five different environments. The environments differed in the density and ratio of energy sources and obstacles. To assess the diversity of the evolved behaviour strategies and allow a comparison to the results of the previous section, the same measure of ‘across-population’ diversity was applied. The different environments used are listed in table 8.3.

Individual simulations were run until a lineage reached PG 2000. At that point, a snapshot of the system was taken, and the population and agent data (described in table 8.1 of the previous section) were recorded. Figure 8.7 illustrates the average number of simulated time steps until PG 2000 was reached and thereby gives an impression of the relative 'difficulty' of the different environments to establish a sustained population.

Table 8.3: Five different environments with varied energy source/obstacle ratio and numbers.

	Energy Sources	Obstacles
E1	100	100
E2	100	50
E3	50	0
E4	50	100
E5	50	50

Most noticeable, for the first three environments (E1-E3) there are no significant differences in the required simulation times. Environment E3, with relatively few energy sources but no obstacles, is equally 'benign' as the two environments with a high resource level. Additionally, the number of obstacles has no measurable effect on simulation time in those two environments (E1 and E2). On the other hand, in environment E5 which contains 50 energy resources and 50 obstacles, simulation time is significantly higher. Finally, as expected, environment E4 with 50 energy resources and 100 obstacles is the 'hardest' environment.

With respect to trends in evolved population properties and morphological aspects, the picture is less extreme. Figure 8.8 shows the average values for a number of quantities. As could reasonably be expected, the average number of agents in a population (upper left) depends on the amount of available resources. It is possibly

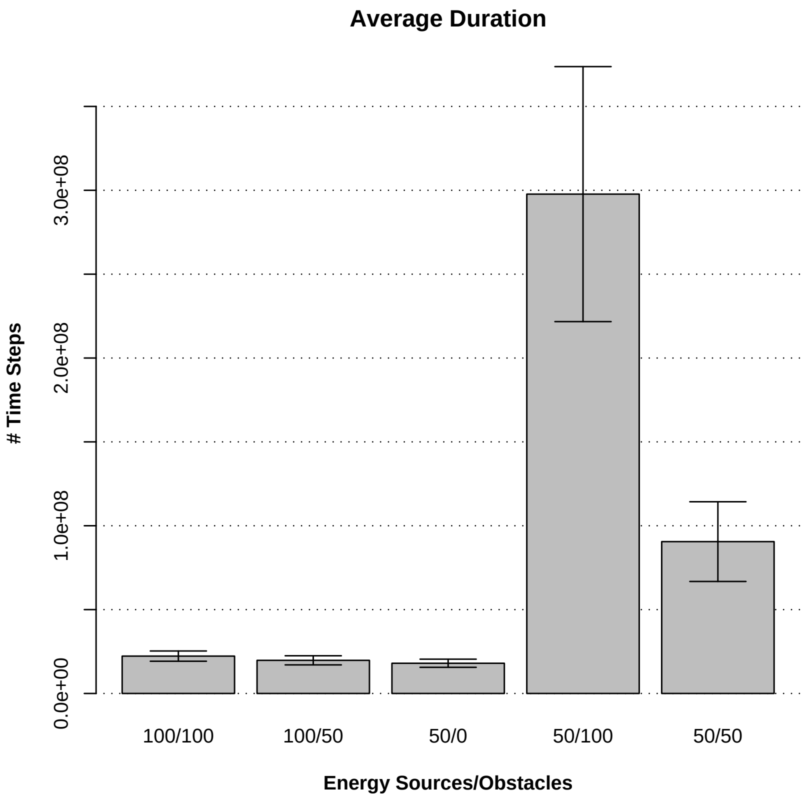

Figure 8.7: Average number of simulated time steps necessary for a lineage to reach phylogenetic generation (PG) 2000. Environments where resource levels are high and the environment without obstacles require much less time to establish a sustained population compared to the two runs with fewer resources (Error bars indicate the 95% confidence interval).

more surprising that it appears to depend on this quantity alone while the number of obstacles in the environment has no effect on the size of the population at all. For the number of offspring (upper right) and the average size (lower right), there are no highly significant differences across the five experimental conditions. The only trends that can be observed are that agents evolved in the 'harsh' conditions (E4 and E5) are slightly smaller and produce significantly more offspring than pop-

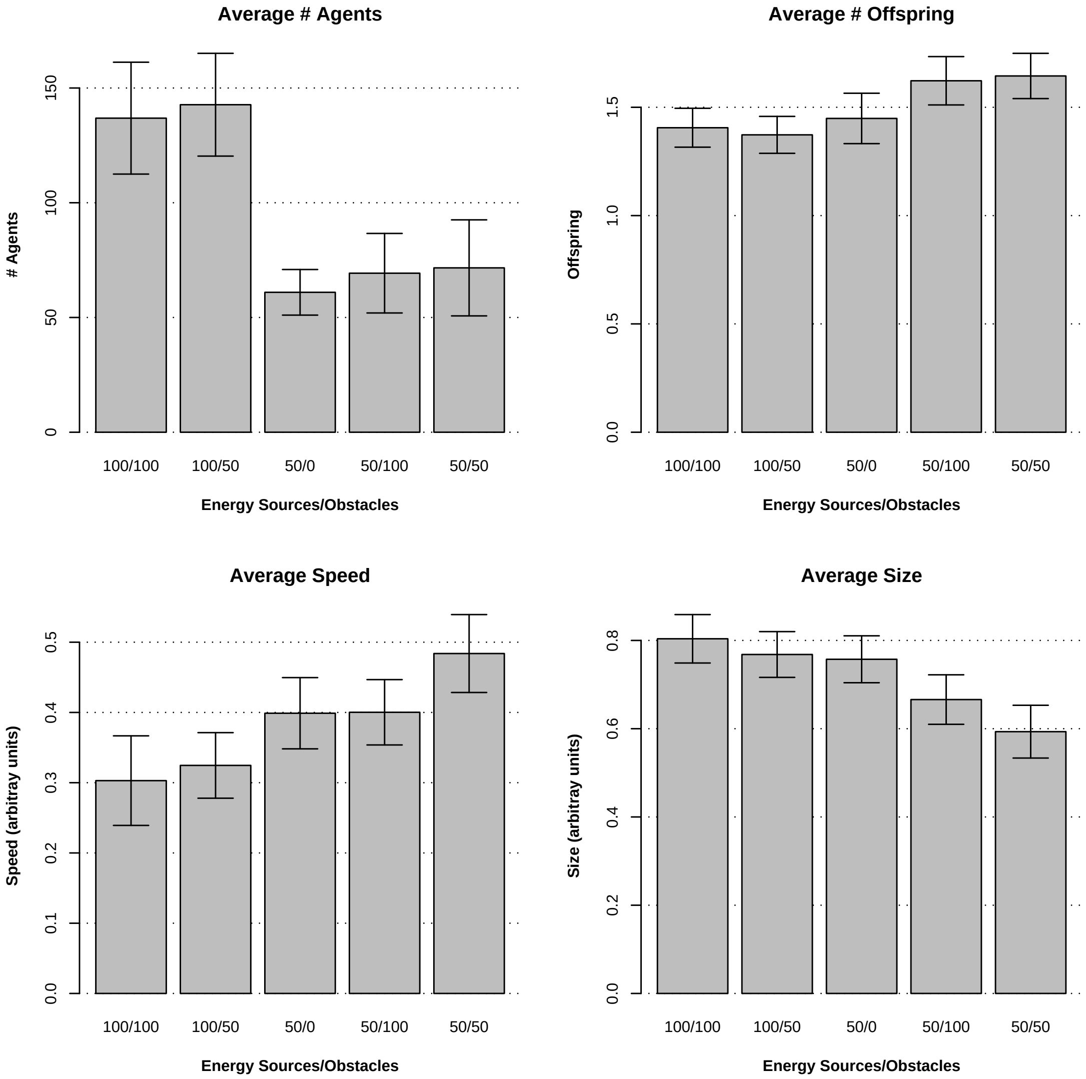

Figure 8.8: Statistical data collected under five different environmental conditions (Error bars indicate the 95% confidence interval). The average number of agents in a population (upper left) depends only on the amount of energy in the environment. In contrast, the environmental conditions have a less pronounced impact on average number of offspring per agent (upper right) and the morphological properties solidness (lower left) and size (lower right).

ulations in the first two 'benign' environments (E1 and E2). Finally, the average speed of the agents is largest in E5 (significantly so, at least with respect to E1 and E2). On the one hand, this is consistent with their smaller size (small agents use less energy at the same speed), on the other hand this seems to be a result which contradicts the findings in (Todd and Yanco 1996), where the authors report that agents moved more at high resource densities and less at low resource densities. The most likely explanation for this difference in result is that they used static environments whereas energy sources randomly relocate to new positions in this scenario. If a resource stays in the same spot forever, it makes sense not to move at all if resource density is low. However, in the case where food sources are not permanently tied to a fixed position this strategy does not work[1].

8.4.2 Results: Energy Resource and Obstacle Density Does not Affect Diversity

Even though the tested environmental conditions range from fairly benign (E1-E3) to considerably harsher environments (E4 and E5), the overall impact on the diversity of observed behaviour strategies was surprisingly small. Figure 8.9 shows the results for the measure of diversity introduced in section 8.2. Both the raw and the normalized entropies show no clear differences in diversity for varying cluster size.

These results are consistent with visual inspection of populations evolved under different conditions. The four main behaviour strategies (Drifter, Forager, Avoider, and Allrounder) could be observed in all settings with the majority of populations

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[1] This was exactly why the mechanism to relocate energy sources was introduced. It is justified because the model was designed to evolve complex adaptive behaviour, and the locomotive effectors are the only means to generate active behaviour. Therefore, while the evolution of sessile strategies is certainly of interest in an ecological model, they were not considered in these experiments.

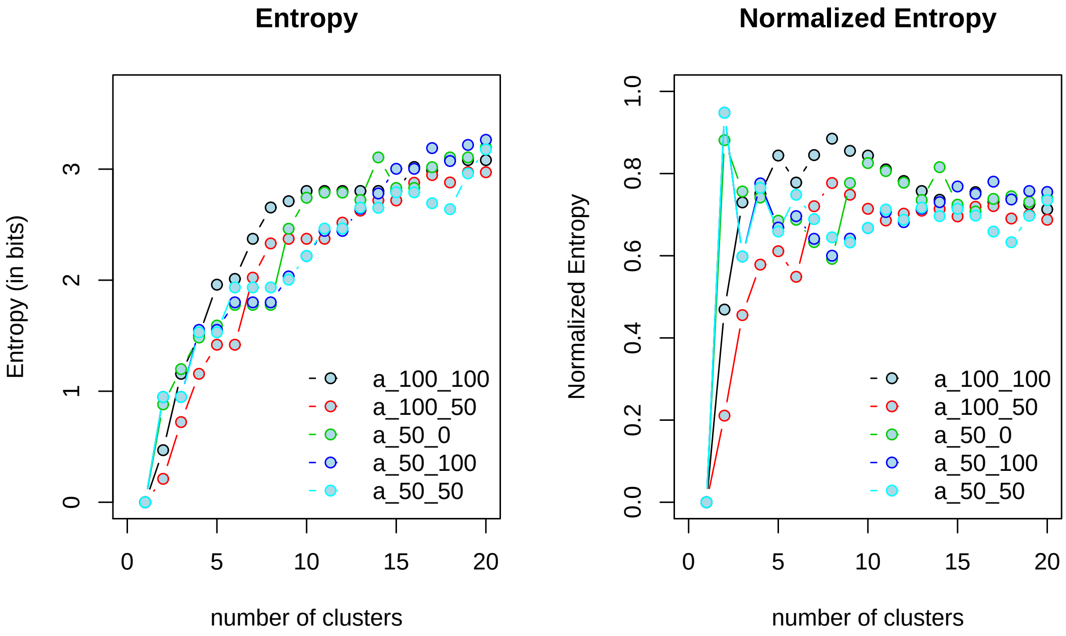

Figure 8.9: Entropy (left) and normalized entropy (right) of combined population and morphological properties (see table 8.1) for an increasing number of clusters ($k \in [1..20]$). Overall, the values show no significant differences in the diversity of evolved strategies across the five experimental conditions.

exhibiting both obstacle avoidance and foraging behaviour. Interestingly, obstacle avoidance behaviour was not less likely in environment E3 which did not contain any obstacles.

The most probable explanation for this fact is very likely also the reason behind the general lack of impact on the diversity of evolved strategies that the various environmental conditions had: once a sustained population is established, from the perspective of an individual agent the other agents themselves make up the most dynamic and 'complex' part of the environment. Obstacle avoidance behaviour, for example, is as likely to evolve as a response to other agents as to static objects in the environment.

Another possible explanation for the relative insensitivity of evolved strategies to environmental variation is provided in (Todd and Yanco 1996). The authors suggest that the possible behaviours of an agent, and the resulting behaviour strategies, constrain the aspects of the environment the agent actually experiences. Consequently, the behaviour itself feeds back to the (subjectively) constructed environment the population adapts to, making the evolved behaviours less sensitive to changes in the environment. What they call "behavior-environment selection-adaptation loop" (Todd and Yanco 1996) is very close to the construction of *umwelt* described in section 3.3.3.

8.5 Discussion

To emphasize the possible impact of design decisions on the algorithmic level of an artificial evolution system, the consequences of the choice of reproductive mechanism have been contrasted with the results of a set of experiments where environmental parameters were varied. The results indicate that for the evolution of diverse behaviour in an artificial system, design choices external to the intrinsic dynamics of that system can potentially have a much greater impact than varying parameters within the system.

Computational models of evolution necessarily include a multitude of design decisions and abstractions with respect to genetic encoding, variability operators and selection mechanisms. The presented experiments show that, in an artificial ecosystem based on natural selection, the method by which agents reproduce has a significant influence on the diversity of the evolved populations. This fact suggests that the reproductive mechanism is an important factor and should receive more attention when designing an artficial evolution system than it has been given in existing literature. As one specific aspect, I have shown that the reproductive mechanism critically impacts the diversity of observed behaviour strategies. The results indicate that decoupling individual survival from reproductive success is more conducive for the evolution of different survival strategies compared to the other two mechanisms which lack such a decoupling, as it allows evolution to explore the trade-off between individual survival and reproductive success.

These findings also suggest that, when simulating evolutionary dynamics, replacing explicit fitness evaluation (as in genetic algorithms) with endogenous fitness is not necessarily enough to tap the 'creative power' of evolution. At every point where *ad hoc* design decisions are necessary, these are likely to have specific consequences for the system. Thus, the choice of reproductive mechanism in systems where the evolving entities are not truly self-replicating introduces another set of biases which can hinder or enable natural selection to take different alleys. This is important to have in mind when designing any artificial evolution system where one is interested in diversity of evolved products.

More importantly, however, this has implications for Alife models used to test hypotheses about biological evolution (for example (Lenski et al. 2003, Taylor and Hallam 1998)). The designers of such experiments have to be careful that the Alife model in question is actually capable of simulating the desired dynamics, and that possible findings are not simply artifacts of the particular set of biases introduced through the choice of the reproductive mechanism.

Chapter 9

Summary, Conclusions, and Future Research

9.1 Summary

The main focus of this work was to describe the requirements for building an artificial evolution system to generate agents that exhibit adaptive behaviour. The major concern was neither to generate agents optimized towards performing a specific task, nor to provide a detailed model of specific ecological phenomena. Instead, the goal was to first identify the crucial design considerations for an evolution system with long-term adaptive evolutionary dynamics and then produce a concrete implementation based on these findings that can be evaluated against the targeted objectives.

I first reviewed existing literature on evolutionary algorithms in chapter 2. Particular attention was paid to the application of evolutionary algorithms as a method to evolve neural networks (neuroevolution) as control systems for autonomous agents.

The problems of explicit objective functions in simple evolutionary algorithm approaches to provide long-term gradients for the evolution of general behaviour were discussed along with some attempts to alleviate those problems. In the first method, incremental evolution, the problem of increasing task complexity was addressed by behavioural or temporal decomposition of the target task into simpler sub-tasks. The second method, coevolution, was proposed to exploit evolutionary 'arms race' (Dawkins and Krebs 1979) dynamics, where two (or more) competing populations are intended to gradually drive each other to ever increasing performance in some target task. Finally, a brief summary of evolutionary ecosystems was given. These approaches are based on the modelling of a system where evolution by natural selection can occur. The chapter concluded with a brief overview of the field of Artificial Life (Alife) because much of the work relevant for this thesis is conducted and published in close association with this field.

The chapter concluded with an overview of several existing computational ecosystems: a short description of *Tierra* (Ray 1991b) was provided mainly because of its importance for stimulating research on computational ecosystems; *PolyWorld* (Yaeger 1994) was discussed because it is the system closest to the one introduced in this thesis with respect to the interpretability of behaviours, and results can therefore, to some extent, be compared directly; finally, *Geb* (Channon and Damper 1998a) was described because it shares with the approach discussed in this text the expressed goal of creating long-term adaptive evolutionary dynamics. Also, to my best knowledge, it is the only other system to be classified as exhibiting unbounded evolution according to the Bedau-Packard evolutionary activity statistics (Bedau et al. 1992, Channon 2001a).

In the following chapter 3, I described Darwin's principle of natural selection and the conditions under which evolution by natural selection can occur, followed by a brief definition of the term *ecosystem*, as used in ecology. The main body of the chapter (section 3.3) attempted to lay out the crucial considerations for designing a computational ecosystem capable of exhibiting long-term adaptive evolution of agent behaviour. A definition of the term and of the function of behaviour was provided, followed by a description of the influence of environmental structure on the evolution of behaviour. The importance of the distinction between a behaviour and the agent-side mechanism subserving this behaviour was discussed, and possible ways of understanding how the two relate to each other were explored. A description of the term *Umwelt* (von Uexküll 1956) was followed by the development of the related argument that for an evolution system designed to exhibit long-term adaptive evolutionary dynamics, it is indispensable that the evolving entities constitute coherent, functional wholes at all times of the process.

I then went on to introduce my model for an evolving computational ecosystem. After an introductory discussion of design goals and expected emergent behaviours, the chapter described the environment, the agent constituents and their interrelations which link all system components to the unitary resource ('energy'). This was followed by a description of the reproductive mechanism which was introduced to decouple individual survival from reproductive success with the aim of increasing the number of available reproductive strategies. The chapter concluded with an overview of the algorithmic evolution mechanism of the system.
The major contributions in the design of the system resulting from the discussion in section 3.3 were:

- To *facilitate the interpretation* on the agent-level, the abstract physical laws underlying the dynamics of the system were defined in a way that aimed to preserve the causal coherence with an observer's intuitions while at the same time ensuring computational tractability.

- To allow for *smooth evolutionary gradients*, agents were evolved as coherent, functional wholes, without any predefined functionality above the level of elementary components.

- To provide *high structural freedom*, all agent parameters and constituents (morphological properties and neural controllers) were linked to the 'physical laws' of the virtual world and completely under evolutionary control.

- To *avoid restricting* the agents to preconceived behaviour primitives (e.g., move, turn, fight, etc.), all behaviour was implemented through a simple but versatile model of locomotive effectors.

- To *increase the diversity* of viable strategies, a reproductive mechanism was introduced that decouples individual survival from reproductive success.

The subsequent three chapters summarized the results of a series of experiments in what was hoped to be a logical succession. First, the observed behaviours were described and behavioural strategies were related to underlying mechanisms and evolved morphological properties (chapter 5). Secondly, the evolutionary dynamics were evaluated with a number of measures to gave evidence for long-term adaptive evolution in the system (chapter 6). Thirdly, an attempt was made to relate observed behavioural complexity to the complexity of the underlying mechanisms using measures of neural complexity developed in (Tononi et al. 1994), and general trends in the evolution of neural complexity were discussed (chapter 7). Finally, the impact of changes on various levels of the system was evaluated.

In more detail, chapter 5 illustrated different behaviour strategies evolved in a number of simulation runs. The observed behavioural strategies were described on a behavioural level, and some attempts were also made to discuss the agent-side mechanisms subserving the behaviours. More generally, the relationships between observed behaviour strategies and evolved morphological configurations were described. I concluded that the main behaviour strategies could be categorized into four distinct classes by observation, and showed that this intuitive classification coincided with a more formal classification based on morphology.
In the subsequent chapter, I evaluated the evolutionary dynamics observed in the system. The Bedau-Packard (Bedau et al. 1992) statistics of evolutionary activity were implemented, and evidence was given that the system exhibits the same type of unbounded evolution as *Geb* (class 3b). Further evidence for the presence of lasting Darwinian evolution was given using another measure proposed in (Miconi 2008b). Finally, some general trends in the evolution of morphological properties of several populations were contrasted with a neutral random-selection run to highlight the concrete effects of natural selection. The experiments in chapter 7 aimed at addressing whether the observed complexity of evolved behaviours is really the result of adaptive evolution. I summarized the general discussion on trends in complexity in biological evolution and described measures of neural complexity and integration (Tononi et al. 1994) which were previously applied in *PolyWorld* (Yaeger and Sporns 2006). Unlike in *PolyWorld*, where no significant increase in integration and only a moderate increase in complexity could be observed, I showed that in my system

both quantities substantially increased over the entire observed period as a result of gradual adaptive evolution. The remainder of the chapter discussed how observed behavioural complexity was reflected in the measured values of complexity.
Specifically, I gave evidence that the appearance of qualitatively new behaviour was accompanied by sudden increases in neural complexity followed by a consolidation phase where complexity decreased. The data also showed that in these experiments low values in the two measures reliably indicate low behavioural complexity. However, I also pointed out that the two forms of complexity did not always coincide: an increase in neural complexity did not necessarily correspond to subjectively complex behaviour. In conclusion it was noted that while the applied measures were useful to shed light on the complexity of the agent-side mechanisms of certain behaviours, they cannot be taken as measures that indicate adaptive success.

The final set of experiments discussed in chapter 8 were performed to assess how the choice of reproductive mechanism impacts the evolutionary dynamics of the system. I tested the hypothesis that my mechanism which decouples reproductive success from individual survival allows more diverse adaptive strategies. The comparison with two mechanism without such a decoupling yielded a clearly positive answer. The second part of this chapter contrasts the impact of the reproductive mechanism with the effect of changes on another level of the system, namely that of different resource and obstacle densities and ratios in the environment. The conclusion was that a design decisions on the ‘algorithmic’ level had a much greater impact on the evolutionary dynamics than the different environments tested. This emphasized the importance of taking into account all aspects of an artificial evolution system when evaluating its evolutionary dynamics.

9.2 Conclusions and Future Research

I set out to clarify and expand the main design requirements that need to be considered in the design of an artificial evolution system if it is to exhibit long-term adaptive evolution of autonomous agent behaviour. The goal of this exercise was to contribute towards the goal of implementing open-ended evolution in an artificial system. The design of the model proposed to test those criteria built on previous models. In particular, I attempted to incorporate the two requirements proposed (but not implemented) by Channon, namely behavioural transparency and an open range of low-level actions (Channon 2001a), as well as the potential for ecological interactions and the competition for energy which Taylor (1999) suggested as improvements to his own model. In addition to that, I added two further criteria to the list of requirements:

- The decoupling of individual survival and reproductive success. This has proved conducive for increasing the number of available evolutionary trajectories. Future experiments could further explore the role of this feature. For example, one could imagine putting this decoupling itself under evolutionary control to determine to what extent it would actively be selected for. Additionally, the reproductive strategies evolved in this model could also be investigated with respect to their relevance to r/K selection (Pianka 1970).
- The importance of enabling the system to provide smooth evolutionary gradients. This demand for smooth evolutionary gradients is felt to be the most

> crucial (even though slightly in danger of being circular). It is also arguably the most difficult to achieve as it is not a property of a particular component (like the type of genetic encoding used) but a property of the whole system that permeates each aspect of the system. For example, on the one hand, predefined structure (e.g., a very elaborate robot body) can create insurmountable bootstrapping problems (Funes and Pollack 1997) rendering the most sophisticated genetic encoding useless. On the other hand, if the gradual nature of evolution is respected through the design of all aspects of the system, the work in this thesis has shown that even a simple direct encoding without crossover operators can support unbounded evolutionary dynamics.

My initial assumption that the biotic selection pressures resulting from direct interaction and competition between agents, combined with the open range of low-level actions would support a range of ecological interactions (e.g., predator-prey relationships, food-webs) could not be confirmed by strong evidence. Even though collective behaviour and some direct interactions between agents could be observed in individual runs, this could not routinely be identified and was difficult to analyse in detail. There are numerous possible explanations for this. One could simply be that such complex ecological relationships simply did not regularly evolve due to the fact within a single run all agents followed similar strategies and belonged to the same lineage. This was mainly due to relatively small and homogeneous environments and therefore, the small population size they supported. Future experiments could aim to increase within-run diversity by varying environmental configurations to increase spatial heterogeneity, include different resources, and increase the size of the virtual world to enable niche creation and encourage speciation.

However, another explanation could be that ecological interactions did evolve but I failed to observe them because the metaphor for interpreting the evolved behaviours broke down at a certain point. Such a failure to identify behaviour would have resulted from the same difficulties with interpreting behaviour as were encountered by Channon (2001a) and Taylor (1999) during the analysis of their respective systems. The elements and rules of the system were defined in a way to 'afford' certain individual behaviours which could readily be identified (e.g., approach and avoid behaviour). However, in a complex system this does not guarantee that cause and effect are always easy to understand and it is easily possible that many ecological interactions simply could not be identified by casual observation. The diversity and complexity of strategies and the large amount of data makes even the rigorous analysis of individual agents infeasible, and certainly much more so the analysis of all ecological relationships between the agents, particularly when it is unclear how these relationships might look. This would suggest that future models which aim at the study of ecological interactions should be based on a metaphor and include components which allow an interpretation of possible interaction of this kind much in the same way that this model afforded the interpretation of individual behaviours.

Despite these difficulties, the model can be viewed as a success with regards to getting closer to implementing an artificial system which exhibits long-term evolution of qualitatively novel and observable behaviours. Now that we are able to build models which classify as unbounded according to Bedau and Packard's evolutionary statistics (Bedau et al. 1992), it might be necessary to develop new methods for assessing the dynamics of evolutionary systems which allow finer qualitative conclusions about the nature of the evolutionary process and which are more sensitive or restrictive in detecting the difference between artificial evolution and evolution in the biosphere. As a step in this direction, Channon (2002) has proposed some modifications to the original evolutionary activity statistics (Bedau et al. 1992). His first of two main criticisms of the original measures concerned examining the mean cumulative activity which, in a system with bounded diversity, can increase unboundedly if one component is retained indefinitely. His proposed solution was to measure *median* cumulative activity instead. His second concern was that, over time, the neutral shadow 'drifts' away from the real run and eventually may lose its comparative relevance (Channon 2001a) for normalising the components. He proposed to normalise activity at the level of components and 'reset' the shadow immediately after each measurement is taken to the data of the real run. Stout and Spector (2005) have analysed this improved version of the activity statistics and found that they were unable to deliberately generate 'false positives', concluding that the measures are robust against trivial systems exhibiting unbounded (class 3) dynamics. In the future, a more complete analysis should include this improved method of measuring evolutionary activity.

Finally, it must be concluded that despite major progress, there is certainly much more ground to cover, both, with respect to isolating the minimally-enabling criteria for an open-ended evolution system, as well to designing artificial evolution systems which generate behaviour of the complexity and robustness of even the most frugal products of its natural counterpart. However, much progress has already been made and I hope that the arguments and evidence given in this thesis provide a helpful contribution towards this end.

Appendix A

Previous Version of a Model for an Evolving Ecosystem

The following section highlights the relevant differences between the previous version of the evolution system which was used to generate the data in chapter 5 and section 6.4 and the model introduced in chapter 4. The description is an adapted version of the model published in (Pichler and Cañamero 2007) and (Pichler and Cañamero 2008).

A.1 Morphology

The morphology of an agent is defined by the properties of its virtual body and the number and position of its sensors and effectors. We use a simple circular shape for the agent's body but both the arrangement of sensors and effectors as well as the configuration of other body properties are completely open to evolution. Thus, at least theoretically, a vast number of different morphologies is possible.

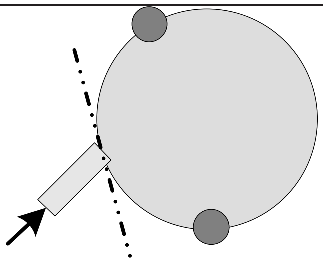

Figure A.1: Exemplary body of a first generation agent with two sensors (round) and one effector (arrow indicates impulse direction).

A.1.1 Body Properties

A circular shape was chosen for the basic body plan because it is generally considered the most neutral form with respect to symmetry; with a circular body the agents have no predefined direction and are rotationally symmetric. Preferred direction of movement and possible symmetry properties are evolutionary emergent and determined by the placement of *external sensors* and *effectors*. Both external sensors and effectors can be situated anywhere along the circumference of the agent's body. To avoid confusion we emphatically call attention to the fact that it was not our aim to implement our model in a realistic or transferable fashion. Where ever it was easily possible, the dynamics loosely resemble our real world intuitions, but in principle our system implements an arbitrary and independent virtual world. However, each of these properties have different metabolic consequences for an agent, discussed in section A.3.

The free parameters are initially set to random values within their defined range.

- *Size:* The size $s \in [0, \infty)$ defines the radius of the body.
- *Solidness:* The solidness $\rho \in (0, 1]$ is a free parameter.
- *Mass:* The 'mass' m of an agent is a function of its size and solidness with

$m = \rho \cdot \pi s^2$

- *Energy Capacity:* The energy capacity $C = \sqrt{m}$ is the maximum amount of energy an agent can accommodate.
- *Maximum Absorption:* The maximum amount of energy $\Delta\epsilon(t)$ an agent can absorb from an energy source per time step is given by:

$$\Delta\epsilon(t) = \min(c_\epsilon(1 + \pi s^2), C - E(t)) \tag{A.1}$$

where c_ϵ is a proportionality constant and $E(t)$ is the energy level of the agent at time t.

A.1.2 Sensors

We provide two predefined groups of sensors which can help the agents make use of different sources of information. Generally, sensors act as input nodes to the neural controller network of the agent. The first kind are *internal sensors* which provide information about the agent's own internal variables. There is one internal sensor for the current energy level and one for the current level of the reproductive depot. Internal sensors are fixed parts of the input layer of the initial controller networks. Even though they cannot be removed by evolution, they are not necessarily connected to the rest of the network, therefore it is not predetermined whether or how they are used.

The second basic kind of sensors are *external sensors*. As the name suggests, these sensors allow an agent to perceive information present in the environment. The environment provides sensory information on three different channels (energy content, solidness, and size). In order to make use of these signals, an agent must evolve the appropriate sensors. An external sensor of type i responds to the i-th channel of an object. The information provided by a single channel is one-dimensional and can roughly be thought of as a chemical gradient. The response r of the i-th channel of an object o depends on its value $v_{i,o}$ and the distance d_o between the sensor and the object. It is given by

$$r_i = \frac{v_{i,o}}{1 + c \cdot d_o^2} \tag{A.2}$$

Hence, the total activation of a sensor S of type i follows from the accumulation of the responses of all objects within a maximum range.

$$S_i = \sum_{o \in O} \frac{v_{i,o}}{1 + c \cdot d_o^2} \tag{A.3}$$

where O is the set of all objects within said maximum range, and c is a proportionality constant.

The relationship shown in (A.3) leads to a sensory response landscape which is further illustrated for a single channel in fig. A.2. In the case of another agent, the energy channel corresponds to the agent's energy depot instead of its current energy level. The intuition behind this choice is that the energy channel contains information about '*potentially consumable energy*'. The energy of the corpse of an agent relates to its energy depot level at the time of death.

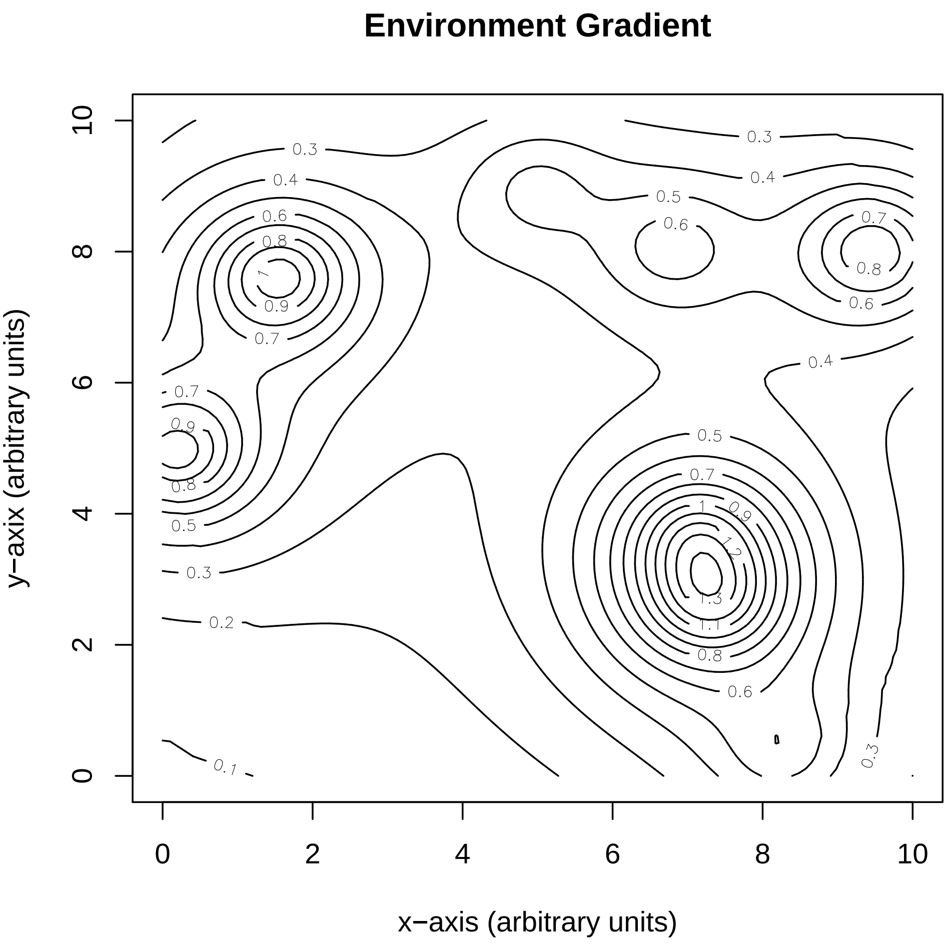
Environment Gradient

Figure A.2: Extract of an exemplary environment. All object properties (solidness, energy signature, velocity, agent) constitute information modalities which can be perceived as an environmental gradient by sensors that respond to the respective modality. The intensity of the stimulus is inversely proportional to the square of the distance between sensor and object.

A.1.3 Effectors

Effectors are a predefined structure to enable the evolution of locomotion in the agents. They are very simple in order to allow basic forms of locomotion but can be arbitrarily combined to implement more complex movement strategies. As with sensors, effectors are nodes in the neural controller network. However, they differ by being located in the output layer. Additionally, effectors are defined by their position on the agent's body and the angle formed by the tangent of the body at that point (see fig. A.1). Hence, the influence of an effector is fully described by its position, its direction, and the strength of its activation. This results in a movement vector $\vec{v}$ for each effector:

$$\vec{v} = \begin{pmatrix} -\sin(\Phi + \alpha + \beta) \\ \cos(\Phi + \alpha + \beta) \end{pmatrix} \tag{A.4}$$

where Φ is the rotation of the agent, α is the position of the effector on the agent's body ($0 \leq \alpha < 2\pi$), and β is the angle of the effector ($0 \leq \beta < \pi$) with respect to the tangent of the agent's body at its position. This movement vector $\vec{v}$ is normalized and scaled with the activation of the effector to yield the final movement.

This allows us to calculate a translation and rotation component for every effector corresponding to its activation. Thus, the overall movement of an agent can be obtained by integrating over all effectors. The effects of multiple effectors on the position $\vec{P}$ and the rotation Φ of the agent at time step t are as follows:

$$\vec{P}(t+1) = \vec{P}(t) + \sum_{i}^{|A|} \frac{\vec{v_i}}{|\vec{v_i}|} \cdot c \cdot o_i \tag{A.5}$$

$$\Phi(t+1) = \Phi(t) + \sum_{i}^{|A|} c \cdot o_i \cdot \cos(\beta_i) \tag{A.6}$$

where A is the set of effectors, o_i is the activation of the i-th effector, and c a proportionality constant.

In case of collision the translation component is reset and only the rotation component is applied. One aim in designing the effectors for this experiment was to avoid the usual Braitenberg-type, two-wheeled design which in our view restricts the freedom of evolution and introduces unnecessary design bias by pre-specifying a bilaterally symmetrical body plan. Our effectors can be thought to act like small jets or flagella. An agent can possess any number and configuration of effectors and is therefore less restricted in the locomotion strategies it applies.

A.2 Neural Controller Networks

The agents are controlled by a neural network. The structure and properties of these controller networks are evolved. We use nodes with piecewise linear transfer functions where two parameters define the operating range of the neuron. Both of these parameters are initially random and evolved for each node individually. A link (synapse) is defined by a real valued weight $w \in (-\infty, \infty)$ and the two nodes it connects. Weights are at present heritable, no lifetime learning takes place. During reproduction not only parameters of existing structure can be modified, but also all components can be added or removed by mutation operators to form *completely arbitrary* (also recurrent) network structures.

First generation agents start out with a minimal network that consists of three fixed nodes and a small random number of sensors, effectors, and connections (see fig. A.3), all initially set to random values.

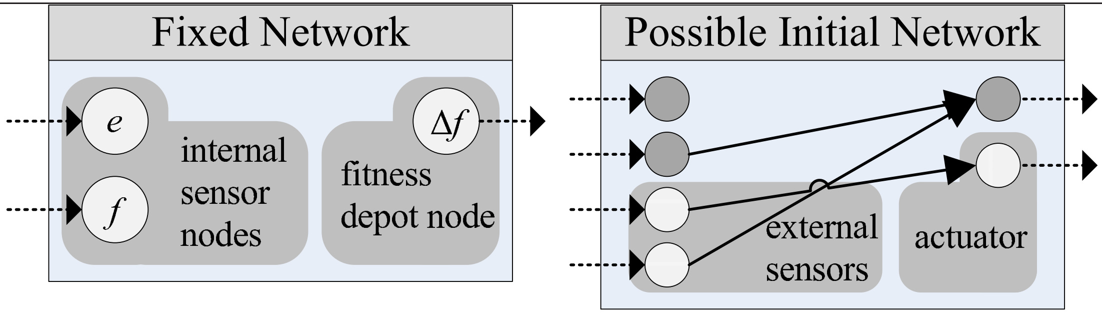

Figure A.3: Controller networks have two fixed internal sensor nodes (energy level e, depot level f) and the depot node Δf in the output layer (left). Additionally, every first generation agent is initialized with a (small) random number of sensors, effectors, and connections (right); All parameters are randomly initialized.

A.3 Metabolism

Energy is the limiting resource that drives the evolution, and because it is the only resource, every aspect of an agent is somehow connected to its energy budget. Every property and every structural component has an effect on an agent's metabolism. This is necessary in this model to create an evolutionary gradient.

The metabolism of an agent has a constant and a variable component. The constant part M_{const} depends on the properties of the agent's body (i.e. its mass m) and the number of nodes $|N|$ and links $|L|$ in the neural network, while the variable part consists of the effector activation and the activation of the controller network. The relationships are given by:

$$\begin{aligned}
M_{const} &= \sqrt{c_1|N| + |L|} \cdot c_2 + m \cdot c_3 && \text{(A.7)} \\
M_{act} &= m \cdot c_4 \sum_{i}^{|A|} o_i && \text{(A.8)} \\
M_{net} &= c_5 \sum_{i}^{|N|} o_i && \text{(A.9)} \\
M_{total} &= M_{const} + M_{act} + M_{net} && \text{(A.10)}
\end{aligned}$$

where (A.8) sums over the activation o_i of all effectors $|A|$ and (A.9) sums over the outputs o_i of all network nodes $|N|$. The c_i are metabolic proportionality constants.

A.4 Sensorimotor Loop

The sensorimotor loop of the agents includes the following major steps at every iteration of the main program loop. After all the sensors have been updated with the current values, the signals are propagated through the controller network. This results in the current action of the agent being executed after taking any collision management into account. Finally, the energy balance is drawn for the agent and the environment (see section A.5.3).

A.5 Ecosystem Dynamics

Considerable effort has been put into providing potentially rich agent-environment interactions along with a complex agent metabolism to allow for the evolution of diverse and non-trivial survival strategies. Bearing this in mind, computational cost must always be another important consideration in simulation. Since we were primarily interested in observable agent behaviours we chose a foraging scenario with mobile artificial agents because it is a well-studied scenario where some likely behaviours can be partly anticipated and often intuitively interpreted by an observer.

A.5.1 Resource Consumption and Renewal

If an agent collides with an energy source, a certain amount of energy is transferred from source to agent. The amount of energy ΔS_E transferred from a source is determined by the maximum absorption $\Delta\epsilon(t)$ of an agent a as defined in (A.1) but cannot exceed the current energy content S_E of the source at the time.

$$\Delta S_E = \min(S_E, \Delta\epsilon_a(t)) \tag{A.11}$$

Energy sources are therefore exhaustible but they 're-grow' at a slow constant rate μ.

$$S_E(t+1) = S_E(t) + \mu - \sum_{a \in A} \Delta S_{E,i} \tag{A.12}$$

The size of an energy source equals its energy content. An energy source has a solidness of zero and allows an agent to pass through unhindered.

A.5.2 Collision

In addition to stopping the agent, an energetic cost (damage) is assigned to a collision. This cost depends on numerous properties of the agent's body as well as on its speed and angle to the object and thereby 'grounds' its morphology and behaviour in the virtual world. Even though the damage calculation is very simple compared to a physically realistic model, it is differentiated well enough to allow the evolution of very different coping strategies, both on the morphological and on the behavioural level. Especially in the case of agent-agent collisions, a damage model that is connected to the agent's morphology opens the possibility of different interaction strategies. In theory, even the emergent evolution of a predator-prey scenario is conceivable if agents 'deliberately' collide with other agents in order to get their stored energy.

The damage calculation is based on the length of the difference vector between the movement vector $\vec{v}_A$ of an agent A and the movement vector of the object it collides with (which, in the case of an immobile object, is the zero vector). Because the collision management resets the translation component in case of collision, we calculate two damage factors df_E and df_I. The former corresponds to the *effective* movement $\vec{v}_{A,E}$ of the agent and the latter to the *intended* movement $\vec{v}_{A,I}$. The effective movement only has an effect at the time of the actual 'crash'. The intended movement continuously affects the damage while the agent 'pushes' against an object. The two costs are balanced by proportionality constants $c_{d,E}$ and $c_{d,I}$, where $c_{d,E} > c_{d,I}$.

There is no global physics engine that calculates these costs. Instead, agents calculate their portion of a collision for both objects involved during their update cycle.

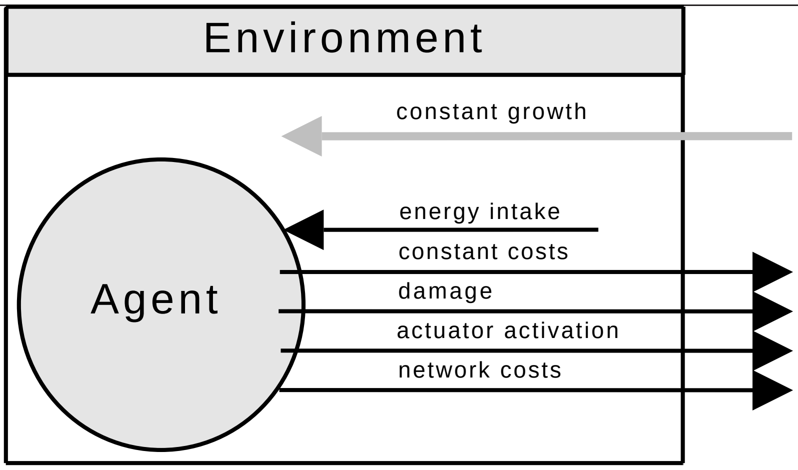

Figure A.4: Total energy balance of agents and environment. The environment acts as source (regrowth) and sink (agent consumption) for energy.

The costs are given by: [1]:

$$df_E = c_{d,E} \cdot \min(|\vec{v}_{A1,E}|, |\vec{v}_{A1,E} - \vec{v}_{A2,E}|) \quad (A.13)$$

$$df_I = c_{d,I} \cdot \min(|\vec{v}_{A1,I}|, |\vec{v}_{A1,I} - \vec{v}_{A2,I}|) \quad (A.14)$$

$$D_{A1 \rightarrow A1} = (df_{A1,E} + df_{A1,I}) \cdot \min(m_{A1}, m_{A2}) \quad (A.15)$$

$$D_{A1 \rightarrow A2} = (df_{A1,E} + df_{A1,I}) \cdot m_{A1} \quad (A.16)$$

where in (A.15) the sum of the two damage factors is weighted by the minimum mass m_{Ai} of the two objects to yield the damage to the colliding agent and (A.16) describes the damage received by the passive agent. If the second agent also actively collides with the first agent (e.g., in a head-on collision) it also calculates a damage.

A.5.3 Energy Balance

The metabolism of the agents together with the described dynamics determine the total energy budget of the ecosystem which is updated every time step. The ecosystem is not a closed system with respect to energy. Energy is added from outside the system through the renewable resources described in (A.12) and dissipates through the metabolic consumption of the agents according to (A.10). A schematic illustration of the total energy balance is shown in fig. A.4.

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[1] For the sake of clarity, another factor to compensate for artifacts of discretization and the sequential update of agents is omitted here.

Appendix B

Software Platform and Parameter Settings

All implementation and analysis involved in the development of this thesis were performed using free or open source software only. The two main implementation parts consist of the ecosystem simulation software and another application to visualize the agents in their environment and their neural network dynamics. Both applications were developed in *Java*[1] using the *NetBeans IDE*[2] on a machine running *Ubuntu*[3] linux.

The main applications can be found in the form of *NetBeans* projects on the CD accompanying this dissertation. Alternatively, they can be requested from the author[4].

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[1] http://java.com/

[2] http://www.netbeans.org/

[3] http://www.ubuntu.com/

[4] p.pichler@herts.ac.uk

B.1 Main Simulation Software

The ecosystem simulator (4500 SLOC[5]) was designed to provide an internal checkpointing mechanism to enable long simulations of parallel runs using the *Condor High Troughput Computing*[6] cluster software. At startup, it searches for two files:

- *current_cp.txt*: This is the checkpoint file (binary) which contains the saved state of the virtual world. It enables resuming or repeating simulations and the inspection of the virtual world at a given point in time.

- *world.conf*: This is the configuration file (ASCII) which contains all parameter settings used in a run. The default values used for the simulations in chapters 6 to 8 are included on the CD. The most important program switches are:

  `PRG_EXPORT`: Globally turns *on* or *off* the export of any data to text files. If *true*, statistical data about the environment and the current population are written to a text file at periodic intervals. If *false*, no file output occurs (including the output below). All statistical output is written in human-readable text.

  `PRG_EXPORT_FT`: Turns *on* or *off* the export of fitness transmission data (see section 6.3) to text files.

  `PRG_EXPORT_EA`: Turns *on* or *off* the export of evolutionary activity data (see section 6.2) to text files.

  `PRG_EXPORT_CP`: Turns *on* or *off* the export of neural complexity data (see section 7.2) to text files.

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[5] Physical source lines of code

[6] http://www.cs.wisc.edu/condor/

`PRG_FINALGENERATION`: Phylogenetic generation number at which the simulation terminates.

`PRG_RUNTIME`: Time (in minutes) at which the simulation terminates.

`PRG_MASTERSEED`: Seed for the random number generator.

Upon termination the current state is written to a checkpoint and a configuration file. To increase computational efficiency and allow execution of the application in the command line (required for the *Condor* cluster), the simulation software was implemented to be independent of the visualization tool.

B.2 Visualization Software

The visualization tool (1600 SLOC) allows to observe the agents in their environment. It was designed to be fairly self-explanatory but a brief introduction to its main functions is given below. The visualization GUI consists of three windows:

- The *control window* allows to perform the general program functions, the most important of which are:

  Toggle: Starts and pauses the simulation.

  Step: Calculates a single time step.

  Write CP: Writes the current state to a file *cp.txt*.

  Read CP: Opens a file dialog to load a checkpoint file.

  Spawn: Turns the MEAM *on* or *off*.

  Slider: Regulates simulation speed.

  Onboard Cam: If an agent is selected, the view stays centered on it.

Capture: Outputs sequentially numbered PNG-files capturing the current view at every time step.

- The *view window* displays the agents and their environment (obstacles in blue, energy sources in green). The mouse can be used in the following ways to manipulate the view, the agents and the environment:

  Scroll button: Zoom in or out.

  Scroll button pressed: Move displayed area of the environment.

  Left button: Select and/or drag objects. Agents can be selected to view their properties in the *agent window*.

- The *agent window* displays the sensors, effectors, and the neural network of an agent including the activation of individual nodes in the main panel. Additional information on the agent is displayed on the side.

In addition to the software developed during this project, the accompanying CD contains video material illustrating the different behaviour strategies discussed in chapter 5[7] and other examples of evolved populations. Finally, the CD also contains a collection of checkpoint files to allow an interactive inspection of evolved agents.

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[7] Created with the older version of the model (see appendix A).

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